UNIVERSITY FOR DEVELOPMENT STUDIES

MODELLING AND FORECASTING MATERNAL MORTALITY AND LIVE BIRTHS – USING VARX MODELS: CASE STUDY OF THE UPPER WEST REGIONAL HOSPITAL

BISILIN ALHASSAN

2021

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UDS/MAS/0045/15

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

SEPTEMBER, 2021

DECLARATION

I hereby declare that thesis is the result of my original work and that no part of it has been presented for another degree in this University or elsewhere. All materials referred to are duly acknowledged in the text. Related works by others which served as a source of knowledge has been duly referenced.

Bisilin Alhassan …… ……

(Candidate) Signature Date

Supervisor

I hereby declare that the preparation and presentation of the thesis was supervised in accordance with the guidelines on supervision of the thesis laid down by the University for Development Studies

Dr. Solomon Sarpong ……. ……..

(Supervisor) Signature Date

ABSTRACT

The Wa Regional Hospital's live births and maternal mortality were analysed and forecasted in this study. The data were obtained from the Regional Hospital and covered the period from January 2009 to June 2020. This study applied Vector Autoregressive with exogenous variable to model the interdependent and dynamic structure that exists between the endogenous variables (live births and maternal mortality) and the exogenous variable (maternal age). Also, the dynamic structure of the observed data was explored using the Granger Causality. On the basis of the observed data, several competing models were examined, and the model selection criteria indicated that the VARX (13, 1) model was the most suitable model to represent the data generation process. The findings from the study indicated that the endogenous variables (live births and maternal mortality) do not Granger Cause each other. This is in confirmation that live births and maternal mortality cannot influence each other for better predictive accuracy or better still, neither variable (live births nor maternal mortality) can get better future values with the inclusion of past values of the other variable. The forecast results confirmed that the predicted values for both variables (live births and maternal mortality) mimics that of the observed values and with the predicted values falling within the acceptable limits.

ACKNOWLEDGEMENTS

My profound gratitude goes to Almighty Allah. It is only by Allah's favour and unconditional amity that I have come thus far with the thesis work. Certainly, I feel indebted in gratitude to my supervisor, Dr. Solomon Sarpong, for his astute insights, inspirations, and unwavering assistance in bringing this thesis to fruition. Certainly, words cannot be used to express my gratitude but all I would say is that may the Almighty Allah bless you. My profound gratitude also goes to all the other lecturers in the Statistics Department most especially HOD, Dr. Suleman Nasiru for his invaluable guidance and assistance offered me in the run-up to this stage of the thesis. I would like to offer my heartfelt gratitude to everyone at the Ghana Statistical Service, Wa, for your unflinching support and encouragement in helping me complete this project. I also extend my gratitude to the entire staff of the Upper West Regional Hospital's Gynecology and Obstetrics Unit for quickly supplying me with the data I needed. Finally, my adored wife and lovely children merit my deepest appreciation for their continued love, prayers, and encouragements.

DEDICATION

This thesis is dedicated to my beloved wife Mrs Fadila Bisilin, mother Hajia Jahara Alhaji Alhassan, and children Rafia Bisilin and Abdul-Rahaman Bisilin.

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
GDHS	Ghana Demographic and Health Survey
GHS	Ghana Health Service
GSS	Ghana Statistical Service
ICD	International Classification of Disease
LB	Live Birth
MA	Maternal Age
MD	Maternal Death
MDG	Millennium Development Goal
ML	Maximum Likelihood
MMR	Maternal Mortality Ratio
MOH	Ministry of Health
PHC	Population and Housing Census
PHS	Public Health Services
UWRH	Upper West Regional Hospital
VAR	Vector Auto Regression
VARX	Vector Auto Regression with exogenous variable

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Maternal death occurs when a woman dies while pregnant or within 42 days after giving birth, regardless of the pregnancy's length or location, from any cause connected to or aggravated by the pregnancy or its management, but not from inadvertent or incidental causes (WHO, 2010).

Live birth is referred to as complete expulsion or extraction from its mother of a product of conception, regardless of the length of the pregnancy, which, following such separation, breathes or displays any other proof of life (WHO, 1950).

According to WHO (2004) publication, sociodemographic factors such as age, access to resources and income level are significant indicators of maternal mortality. Younger expectant women are more likely to suffer from complications and even death through pregnancy than their older counterparts.

According to GMHS (2007) and PHC (2010), there is growing evidence that if the correct emergency obstetric care (EMOC) services are provided at the right time, maternal mortality can be reduced. The onus will now lie on players in the industry to intensify efforts and concentration on availing effective and well-timed delivery of emergency childbirth services (UNDP, 2007; GSS et al., 2008)

According to the UN Millennium Project (2005), most significant obstetric complications cannot not be foreseen or prevented, but they can be successfully

treated provided early access to excellent Emergency Obstetric services and competent attendants are available (UNDP, 2007; GHS, 2008).

The maternal mortality rate in Ghana in 2010 was 350 deaths per 100,000 live births, according to WHO/UNICEF/UNFPA/World Bank (2012) estimates, down from 580 deaths per 100,000 live births in 2007. The maternal mortality ratio of 485 deaths per 100,000 live births appeared to be a fair measure of the level of maternal deaths in Ghana, based on the 2010 Population and Housing Census results. The research also shows that the Upper West Region had a mortality rate of 466 deaths per 100,000 live births (GSS, 2010).

1.2 Problem Statement

In this modern-day world, maternal mortality is believed to be a violation of the women's rights and the mortality rate is regarded as a prime indicator for development of a country. Goal 3 of the Sustainable Development Goals (SDGs) adopted by the global community in 2016 aims to improve maternal health. Countries are expected to reduce maternal mortality to 70 deaths per 100,000 live births by 2030 under SDG3 target 3.1 (WHO, 2015). As a result, countries all over the world have devised programs and policies to combat this nuisance using the resources at their disposal.

Senah (2003) observed that for some societies in Ghana, the death of a woman resulting from childbirth, or any pregnancy-related complications is regarded as a terrible loss, at times demanding complex customary cleansing of the society. Consecutive Governments in Ghana have instituted some policy interventions

all in an effort to curb maternal deaths and morbidity. Building and expanding maternal and child health (MCH) clinics across the country; training of at least 6,000 traditional birth attendants (TBAs); free antenatal care (ANC) and free child delivery policies; and the establishment of the National Health Insurance Scheme (NHIS) are just a few of the interventions (UNDP, 2007; GHS and ICF Macro, 2008). Despite these efforts, Ghana's maternal mortality rate remains high, particularly in the Upper West Region. Mortality and live births affect other levels of the economy especially economic and population growth, and it is important we design a model that can be used to forecast maternal mortality and live birth values for future use by policy and decision-makers at UWRH.

This study, in its literature scout, has realised that little or no research was done on maternal mortality and live births data using the multivariate technique such as VARX. This study is therefore set to bridge this gap by applying a VARX process to model the interaction and co-movements between maternal mortality and live births.

1.3 General Objective

The research seeks to identify a model that best fits the maternal mortality and live births data obtained from the Wa health institution.

1.3.1 Specific Objectives

The study seeks to**:**

1. Determine, empirically, a suitable *VARX* (p, s) model for the live birth and maternal death series.
2. Assess the level and trend of maternal mortality ratios over the study period
3. Establish whether there is a dynamic relationship between maternal mortality and live births.
4. Forecast maternal mortality and live birth cases using the optimal model

1.4 Research Questions

1. Which model best describes MMR and live-births' cases at the UWR Hospital?
2. What is the trend of maternal death ratios over the study period January?
3. What interaction exists between maternal mortality and live births?
4. What will be the patterns and consistency of maternal mortality and live births over the forecast period

1.5 Significance of the Study

The Ghana government is committed to achieving the Sustainable Development Goals (SDGs), specifically goal 3.1, which focuses on improving maternal health and reducing maternal mortality. In view of this, the Government, development partners and other stakeholders have implemented programmes and policies in their quest to achieving maternal health and in effect curtail maternal deaths. The

study believes that furnishing policy makers and stakeholders with relevant statistics in advance will help them better assess the programmes and projects implemented towards achieving the SDG goal 3.1.

This study would therefore provide the desired statistical model that would help churn out future maternal mortality and live birth figures for quick and reliably informed decision-making. The research also served as a springboard for future studies.

1.6 The Scope of the Study

The Upper West Regional Hospital is the largest health institution in the Region. The hospital also functions as a referral Centre for other fringe facilities in Upper West Region, Northern Region, and Burkina Faso. This facility keeps track of a large number of pregnancy-related problems and handles other maternal medical conditions. The study considered only maternal deaths and live births that occurred at the UWRH for the period January 2009 to June 2020. The variables of interest included live births, maternal mortality, and Average monthly maternal age. The monthly live births, maternal death and average monthly maternal age were obtained from the registers of the Gynaecology and Obstetrics Unit of the Hospital from January 2009 to June 2020.

1.7 Limitations of the Study

The study is constrained by information on women who died outside the facility from pregnancy-related causes. Again, the study made use of the computed average monthly ages of these expectant mothers instead of their actual individual ages recorded. Important variables that are associated with maternal deaths such as antenatal attendance, level of education, hemoglobin level among others were not available. Consequently, the study will use the only available information on pregnant women who attended the hospital to deliver within the study period.

1.8 Thesis Organisation

The entire thesis was organised into five chapters. The first chapter included the backdrop of the study, the research topic, the objectives of the study, the significance of the study, the scope, and lastly the thesis organisation. The second chapter looks at related literature based on the study's objectives and the models that could be applied to achieve them. It focused on the global situation of maternal fatalities and live births, as well as the situation in Ghana. The chapter also reviewed related studies on maternal deaths from various institutions as well as the application of vector time series models. Chapter 3 also described the methodology used in the study. It discussed the sample population, the theory and formulation of the vector autoregressive models with exogenous variables, and their expected solutions. The study's data was described, analysed, and the findings were discussed in Chapter 4. Finally, chapter 5 brings the investigation to a close with precise suggestions.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter discussed some literature on the state of live births and maternal deaths at large. It also reviewed numerous sets of literature on the application of models relevant to the theme of this study.

2.1 State of Maternal Mortality and Live Births

About 830 mothers die daily from childbirth complications and avertible causes of pregnancy, despite the 44% reduction in of maternal deaths rate since 1990. This, according to the United Nations Population Fund, is about one woman for every two minutes and 20 or 30 mothers are confronted with severe, or long-long-term complicate

The maternal mortality ratio for Ghana in 2010 was 350 deaths per 100,000 live births, according to a recent WHO/UNICEF/UNFPA/World Bank (2012) estimate, with an uncertainty range between 210 to 630, considering the impact of sampling mistakes (UNFPA, 2017).

Ghana was determined to attain Millennium Development Goal (MDG) 5 and had spent the last two decades focusing on reducing maternal mortality in health facilities (GHS, 2009; NDPC and UN, 2015). Free mother care and National Health Insurance were two policies among others proposed and implemented to

address maternal health issues.

Ghana stated her commitment to meeting the Millennium Development Goal (MDG) 5 in a report by GHS (2015). For the past two decades, Ghana has been working feverishly to reduce maternal fatalities in all of the country's health facilities (GHS, 2009; NDPC and UN, 2015). Free maternal care programs and the National Health Insurance Scheme (NHIS), which have resulted in an increase in contact and use of healthcare services; and midwives learning life-saving skills and the establishment of Prevention-of-Mother- to-Child-transmission (PMTCT) centers and services (GHS, 2005; NDPC and UN, 2015).

Ghana was ranked 32nd on the global maternal death rate index in 2014, according to the CIA. According to the National Consultative Meeting on Maternal Mortality Reduction in Ghana in 2008, the National Reproductive Health Coordinator found that some nations, including Ghana, slipped short of the Millennium Development Goal (MDG) 5. The overall national goal was to reduce the maternal death rate from 214 per 100,000 live births in 1990 to 54 maternal deaths per 100,000 live births in 2015 but fell short off the mark.

Between 2007 and 2010, absolute mortality cases at the Tamale Teaching Hospital decreased from 74 to 33, according to Gumanga et al. (2011). The rate of decrease was however unacceptably slow.

Maternal mortality is defined as death of a woman during pregnancy, birth, and 42 days following delivery or the end of pregnancy, excluding deaths caused by accidents or violence, according to the 2017 Ghana Maternal Health Survey (GMHS) study. Ghana's maternal mortality rate (MMR) was 310 deaths per

100,000 live births in the seven years prior to the study, with a confidence interval of 217 to 402 deaths per 100,000 live births. The MMR point estimates differ zonally, but the confidence intervals overlap, indicating that the differences are not statistically significant (GSS, 2017).

As countries progress from developing to developed ones, they go through three stages of population increase which is high rate of births and high rate of deaths, high rate of births and declining rate of deaths, and low rate of births and low rate of deaths. These theories imply that, couples do not consciously take attempts towards reducing births, but instead give birth to as many children as nature permits during their reproductive years. While the birth rate remains high, the rate of deaths begins to drop as a result of increased medical care, access to more nutritious food, and people leading more sanitary lifestyles, among other factors. Finally, as countries become more developed, the rate of mortality drops to near-zero levels, and couples choose to have fewer children, resulting in low rate of births. With a high rate of birth and declining rate of deaths, Ghana, as a middle-income country, falls into stage two of this theory (Bougangue, 2013).

A mother's death is mainly regarded as a personal tragedy that will exacerbate over time. A mother's death is commonly an emotional crisis in many developing countries, resulting in long-term social and economic disintegration for both the immediate family and the wider community (Tezeta, 2015).

The immediate and long-term ramifications of maternal fatalities were discussed. The death of a mother has a significant impact on the immediate family since it

causes financial hardship. Mothers not only provide care for their families, but they also contribute considerably to household income.

Children whose mothers have died have a higher death rate. Babies whose moms die in childbirth have a much lower chance of reaching their first birthday than those whose moms do not die or die from other causes, according to research. Early marriage has been associated to increased maternal mortality and, as a result, baby and new-born mortality. Another important effect of maternal death has been found as the difficulties of managing the household without the woman. While dads and surviving children are frequently pressed to take on the chores performed by one woman in order to alleviate the burden of caring, children are frequently asked to go in with other relatives, which can further sever family ties (Ononokpono and Odimegwu, 2014).

According to the World Health Organisation (WHO), poorer nations account for 99 percent of all maternal fatalities worldwide. 85 percent of global maternal deaths occurred in two regions: Sub-Saharan Africa and South Asia. With 500 maternal deaths per 100,000 live births (an estimated 162,000 maternal deaths), Sub-Saharan Africa has the highest MMR, followed by South Asia with an MMR of 220. (83,000 maternal deaths). In comparison, in developed countries, the MMR is 12 maternal deaths per 100,000 live births. MMRs, in addition to significant geographical disparities, vary greatly across countries.

Yoko et al. (2011) examined the data quality through the computation of MMR. They discovered in the study that data obtained from the Central for Statistical Office (CSO) and other sources produced contradictory outcomes. In 2005, the

CSO estimated MMR to be 34.8, whereas United Nations Children Fund (UNICEF) and the World Bank estimated it to be 45.0 and 55.0, respectively. They advised that a particular maternal death review committee be established across all health jurisdictions in Trinidad and Tobago as the optimal maternal death review procedure.

Hogan and Foreman (2010) examined maternal mortality levels and trends in 181 countries from 1980 to 2008 in order to objectively examine progress toward Millennium Development Goal 5. They generated estimates of maternal fatalities using robust analytical methodologies. In 2008, they estimated 342,900 maternal fatalities worldwide, down from 526,300 in 1980. The global MMR fell from 422 per 100 000 live births in 1980 to 320 per 100 000 live births in 1990, and then to 251 per 100 000 live births in 2008. Since 1990, the global MMR has been declining at a pace of 1.3% per year. Only 23 nations are on track to achieve a 75 percent reduction in MMR by 2015, according to the study, with nations like Egypt, China, Ecuador, and Bolivia making rapid progress.

Worawan et al. (2007) conducted a study with the goal of calculating the maternal mortality ratio (MMR) from 2004 to 2006 using multi-source data and demonstrating the disparities between the official reasons of death and the research results. Individual civil registration data as well as inpatient records from all public hospitals were used. The civil registration contains information such as a person's personal identification number (PIN) and other personal information. According to their findings, the number of maternal deaths decreased from 362 in 2004 to 330 in 2006. In 2004 MMR in the country dropped from 445 to 41.6 per

100,000 live births. As a result, they concluded that policymakers could gain trustworthy information regarding the causes of maternal fatalities by combining matching techniques with individual data.

Mojekwu and Ibekwe (2012) used simultaneous stepwise multiple regressions to investigate maternal mortality in Nigeria. Their findings revealed that a skilled health professional's delivery and a woman's educational level had a greater impact on lowering the maternal death ratio than other factors.

Fawole et al. (2012) investigated the factors that contribute to maternal death in Nigerian institutional deliveries. Using a stratified multi-stage cluster sampling approach, they discovered 79 maternal deaths and 8,526 live births throughout the study period, resulting in a mother mortality ratio of 927 per 100,000 live births.. Approximately one-fifth of women (20.5%) received no prenatal care, whereas 79.5 percent got at least one antenatal visit during their pregnancy. Normal deliveries accounted for four-fifths of all deliveries (80.5 percent). The rates of elective and emergency caesarean sections were respectively 3.1 percent and 11.5 percent. Maternal mortality was linked to a lack of prenatal care, parity, degree of education, and mode of delivery.

High-income countries have lower MMR ratios than low-income countries, hence socio-economic factors have a big role in boosting MMR (Bhutta et al., 2012). They conducted a global study on reducing maternal, newborn, and infant mortality and discovered that low-income nations have an estimated 500 deaths per 100,000 live births, compared to 4 deaths per 100,000 live births in high-

income nations. Hypertensive illnesses, sepsis/infections, obstructed labor, and abortion-related cases were among the health-related factors that increased MMR.

The impact of DS-related elective pregnancy terminations (after a prenatal diagnosis of DS) on live births with DS was calculated from 1974 to 2010. In the most recent years (2006–2010), the live birth prevalence for DS was estimated to be 12.6 per 10,000 (95 percent confidence interval 12.4–12.8), with roughly 5,300 births per year. Annually, an estimated 3,100 DS-related elective pregnancy terminations were conducted in the United States during this time period. In 2007, the projected rate of live births with DS being reduced due to DS-related elective pregnancy terminations in the United States was 30% (95 percent CI: 27.3–31.9). Their findings and model offered information on the effects of elective pregnancy terminations on live births to children with Down syndrome, as well as a baseline from which future trends in live births to children with Down syndrome might be anticipated (AJMG, 2015).

2.2 Review of Related Studies

Gideon et al. (2015) discovered maternal death to be one of the most sensitive gauges of health inequalities between rich and poor countries in their study "Forecasting Monthly Maternal Mortality in the Bawku Municipality, Ghana using SARIMA."

The study findings underscored the health of an expectant mother as very important to the growth of our economy should therefore be taken seriously. The

study modeled maternal mortality cases from January 2000 to December 2014 at the Bawku Municipal Hospital, Upper East region of Ghana using Seasonal Autoregressive Moving Average (SARIMA). The suitable model found was SARIMA (3, 0, 0) × (1, 1, 2)12. The projected maternal death cases largely exhibited a declining trend, nonetheless, went up in the second quarter and in the last quarter, and that surely should raise eyebrows. The study hoped that future research could join in with studies on maternal mortality data from other regions of the country for an in-depth analysis.

Lu (2001) used a VAR process to analyse the demographic structure of the United States from 1910 to 1990. He also wanted to see if there were any pairwise correlations between the variables of immigration, US population, Gross Domestic Product (GDP) per capita, and birth rate. The findings of the study revealed that the population of the United States was reliant on its own lagged values, as well as those of immigration and birth rate.

Ewing et al. (2007) used a vector-autoregressive process to investigate the dynamic interaction between predator and prey, as well as the system's responses to shocks. From the study, evidence was adduced on the premise that responses of the density associated with the population growth of the predator was significant to shocks in the growth rate of the prey and vice versa. Also, the study did not basically find similar results through the application of the traditional regression technique.

In their bid to model Malaysian financial policy, Raghavan et al. (2009) contrasted three distinct multivariate time series processes, the VARMA, SVAR, and VAR

models. They employed effective money supply, consumer price index, overnight interbank rate, and industrial production as variables. The study adopted plots of response curves of impulses for each of the stated models so as to ascertain the influence of shocks on each of the stated variables. The result from these models favoured the VARMA model such that result of the VARMA model was in line with prior theoretical assumptions.

Rout et al. (2013) in a study made of currency exchange rate in coming out with the best ARMA model that best describe the observed data. The suitable model (adaptive ARMA model with differential evolution-based training with feed forward and feed backward parameters) was considered superior as compared with four other models (ARMA-cat swarm optimisation (CSO), ARMA-forward backward least mean square (FBLMS) ARMA-particle, ARMA-bacterial foraging optimisation (BFO) and swarm optimisation (PSO)).

Chien et al. (2006) employed a Vector Autoregressive Moving Average (VARMA) technique to see if there was any correlation between Taiwanese sales and stock prices recorded on a monthly basis. The analysis revealed a one-way association between stock prices and sales numbers, but no evidence that stock prices were impacting sales.

In a study titled “Forecasting the exchange rate in South Africa: A comparative analysis challenging the random walk Model”. Botha and Pretorius (2009) discovered that the multivariate model (VARMA) outperformed one-variate models (excluding the random walk model) in the short-run and one-step ahead projection. Longer-term forecasts were also said to have performed better using

multivariate models. They proposed that various frequencies be employed to reflect the dynamic interaction between variables in a Structural VAR framework to increase the accuracy of multivariate models in particular. The two approaches to exchange rate forecasting, namely the technical and fundamental approaches, were contrasted in their research. The MAD/mean ratio was used to compare several univariate models, including the random walk model, to many other multivariate time series models.

Sarpong (2012) conducted a study at Okomfo Anokye Teaching Hospital by employing time series and the count regression models. The count regression was utilised in the study to examine the occurrence and incidence of MMR while the time series analysis made use of ARIMA model in forecasting the MMR over a period of time. The analysis on the time series revealed a reasonably steady MMR which was exceedingly high at 967.7 per 100,000 live births. The ARIMA model fitted the data well and has been very useful in a variety of situations. The study went further to suggest that the ARIMA model should not be used when forecasting in the medium to long term. Also with the count regression technique, the data supports the issue of equal dispersion and hence the Poisson regression model was devised in modeling the occurrence and incidence of MMR at the hospital.

Nasiru and Sarpong (2011) collaborated on a study titled "Statistical modeling of hypertension cases in Navrongo, Ghana" in 2011. According to their research, the condition is one of the leading causes of illness and mortality around the world. In Navrongo, the researchers used Box-Jenkins ARIMA models to model and

forecast hospitalisations and outpatient hypertension patients. ARMA (1, 1) and ARMA (3, 2) models were found to be appropriate for predicting and forecasting admission and outpatient cases, respectively. Despite the falling trend of predicted hospitalisations and outpatient hypertension cases, they made an impassioned request to the Ministry of Health and public health professionals to organise educational programmes for indigenes to help reduce the prevalence of hypertension.

In China, a study was carried out in March 2011 to determine the feasibility of ARIMA models towards forecasting maternal death ratios (MMRs). ARIMA model was formed basically using MMR of China in the years 1991 to 2009. The series was smoothed out by employing differencing method and they were able to find the orders of the model. They then used the 2010 national maternal mortality ratio forecast model to assess the forecasted outcome. They discovered that ARIMA model was a good fit, and the resultant residual autocorrelation function indicated the residual sequence behaved like white noise series.

Daniel (2014) in his study entitled "Forecasting Maternal Mortality Ratio in Juba Teaching Hospital" found that there were 135 maternal deaths and about 29,711 live birth deliveries. The study went further to determine the total MMR of 454 per 100,000 live births over the period of consideration (January 2008 to December 2014). Also, the annual MMR on the average over the entire period was 476.6 per 100,000 live births which these statistics were found to be comparatively below the year-on-year average figure of Juba. Similarly, a study in South Sudan found MMR to be 730 per 100,000 live births (MDG report, 2014)

. The report from the MDG also revealed that monthly MMRs could best be predicted by ARIMA (3, 0, 1) model at the Juba Teaching Hospital for the period of January 2015 to December 2015.

International Journal of Energy Economics and Policy in January 2019 carried out a research by applying the VARX model to forecast in the area of energy. In the study, several candidate models of VARX were developed. The analyses from these VARX models favoured the VARX (3, 0) model and hence was utilised in forecasting the energy data. The findings also showed that impulse in PTBA influenced the volatility of HRUM energy even though the HRUM energy remained stable and near zero when a shock in PTBA occurred. The shock in HRUM energy caused PTBA to respond negatively for about 2 weeks, after which the impact became positive for up to 2 years. The volatility was apparently very high (IJEEP, 2019).

In Ghana, Adedia et al. (2018) focused attention on maternal mortality through the application of time series data in a public health facility for a thirteen-year period (January 2000 to December 2013). The data were modelled by employing the ARIMA technique. Based on the application of model selection criteria, the study concluded on the ARIMA (1, 1, 1) as the best model to predict maternal mortality cases in the public health facility.

In other study, Curtis et al. (2013) built a model with the aim of forecasting sales. The data devised for the study was in the retail industry of which a sample of firms were considered. The model built in the study by Curtis et al. (2013) was able to explain the difference between sales growth caused by an increase in the number

of sales-generating units and growth caused by an increase in the sales rate at existing units (e.g. the comparable store growth rate). In addition, the built model considered various sales trends, making it possible for new stores to earn more or less than old stores, possibly because new stores take a long time to mature or because they enjoy early popularity. The result from the sales forecasting indicated that, the errors of the in-sample forecasts to be less than two percent while the errors of the out of sample forecasts were as precise as that of the forecasts for the analyst revenue.

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CHAPTER THREE

METHODOLOGY

3.0 Introduction

The methodology section deals with the methods to be employed, the procedures and tools for analysing the maternal mortality and live-births data obtained from Wa Regional Hospital. Some of the discussion points include among others the approaches used in modeling, and the features that are integrated into the model. To ease off understanding in the somewhat mind-burgling model building procedures, the study would start from the rudiments and gradually build up to the most suitable model.

3.1 Profile of the Study Area

The Upper West Region of Ghana is located in the country's northwestern corner, sharing borders with the Upper East, Savana Region, and Burkina Faso regions to the east, south, and west, respectively. Wa, the regional capital, was established in 1983 by the then Head of State Flight-Lieutenant Jerry Rawlings. The Upper West region was formed from the Upper Region, which is now known as the Upper East.. Agriculture is the primary source of income in the region. Corn, millet, peanuts, okra, shea tree, and rice are among the crops planted. Sheep, goats, chickens, pigs, and guinea fowl are bred primarily for meat and eggs respectively.

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3.1.1 Upper West Regional Hospital (UWRH)

On the health front, the region has 242 health facilities that provide a variety of services throughout the region. Three (3) district government hospitals, one regional hospital, two Christian Health Association of Ghana institutions, and three (3) private hospitals are what made up this number. The Upper West Regional Hospital is the region's largest medical facility. It serves the Upper West Region, parts of the Northern Region, and several Burkinabe settlements as a referral hospital. The hospital first opened its doors in 1919. In 1955, it was renamed the District Hospital, and in 1985, it was rechristened the Regional Hospital.

3.2 Data and Source

Data for the study are entirely secondary, gleaned from the record books of the Obstetrics and Gynecology Unit of the Upper West Regional Hospital for the period January 2009 to June 2020. The study variables are maternal mortality, live births, and maternal age (average) as exogenous variable. A total of 138 (11.5-year-long) data points were obtained.

In this study, the population comprised all pregnant women who visited the Upper West Regional Hospital (UWRH) to deliver from January 2009- June 2020. The study however excluded women who were admitted but did not deliver as well as those who had still-births. The sample data included only three variables. These variables are maternal deaths, live births and average maternal ages of the sampled mothers that visited the UWRH during the study period.

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3.3 Concept of Multivariate Time Series

Multivariate time series is a set of observations on k variables of interest that have been collected in regular time order (usually hourly, daily, weekly, monthly, quarterly, or yearly). Consider the (k x 1) vector time series variable $Z_t = (Z_{1t}, \cdots, Z_{kt})'$, where the i^{th} row of $\{Z_t\}$ is Z_{it} , that is for any time t. Multivariate time series analysis is used when a researcher wants to model and explain the interactions and co-movements among a group of time series variables. Some examples of multivariate time series include unemployment rate and income, inflation rate and exchange rate, consumption, and Gross Domestic Product (GDP) among others. The main objectives of multivariate time-series analysis are to model the dynamic relationships between the variables of interest and to also improve the prediction accuracy of the system variables.

3.3.1 Stationary Theorem

Multivariate time series is said to be stationary if the statistical properties of each of the component time series remain unchanged over time. Thus, the vector time series is only considered stationary when the components are jointly stationary.

The vector time series $\{Z_t\}$ is weakly stationary if the mean, variance and the covariance of $\{Z_t\}$ are time-invariant for all time t. More specifically, $\{Z_t\}$ is second-order stationary if:

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$$E(Z_t)=\mu, Cov(Z_t)=\sum_z=\Gamma_0=E\left[(Z_t-\mu)(Z_t-\mu)'\right], corr(Z_t)=\rho=D^{-1}\Gamma_0 D^{-1},$$

where D is a $(n\times n)$ diagonal matrix with the j^{th} diagonal element

$$D=\left[\text{var}(Z_{jt})\right]^{1/2}.$$

In applications, second-order stationarity enables one to make valid inferences concerning future observations (e.g., prediction) of the underlying process. Understandably, in the condition of weak stationarity, we assume that the first two moments of $\{Z_t\}$ are finite. On the contrary if these moments are not finite then the process $\{Z_t\}$ would be considered non-stationary.

3.3.2 Augmented Dickey Fuller (ADF) and Kwiatkowski-Philips-Schmidt-Shin (KPSS) Test

They are tests of statistical hypotheses that are used for finding out if time series process needs to be differenced or not. In the time series analysis, there exist several stationarity-test packages. In this study, we would restrict ourselves to the ones put forward by Dickey and Fuller (1979) and Kwiatkowski et al. (1992). Separate stationarity test would be applied to each component series of the vector series. The following forms the basis of ADF test.

$$\Delta X_t=\phi_0+\lambda t+\beta X_{t-1}+\sum_{i=1}^{m}\alpha_i\Delta X_{t-i}+e_t\ , \qquad (3.1)$$

The ADF set of hypotheses is as stated by:

$H_0:\beta=0$ (Series contains a unit root) against three (3) alternating alternatives:

i) $H_1:\beta<0$ (Series is stationary, without a drift nor time trend)

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ii) $H_1 : \beta < 0$ (Series is stationary, with a drift)

iii) $H_1 : \beta < 0$ (Series is stationary, with drift and a time trend).

The t-statistic is given as:

$$ADF_\tau = \frac{\hat{\beta}}{SE\left(\hat{\beta}\right)} \quad . \tag{3.2}$$

Since these tests are carried out using the residual terms instead of the unprocessed dataset, it is impossible for t to assume its normal distribution properties to provide critical values. As a result, the statistic t has its own distribution merely known as the Dickey–Fuller table.

The KPSS test was propounded by Kwiatkowski et al. (1992) which test the null hypothesis of stationary series. Consider that the number of observations defined to be H then the test statistics for the test can be given by:

$$KPSS = \frac{1}{H^2} \sum_{h=1}^{H} \frac{S_h^2}{\hat{\sigma}_\infty^2}. \tag{3.3}$$

The test is only rejected for p-values larger than the significant level of 5% considered in this study.

3.4 Granger Causality

The Granger causality test is a hypothesis test used to determine whether the past values of one time series is helpful in predicting another series future values. As vector-series model, VARX model is largely used for forecasting future values of the k-variate data. Thus, if a variable Z_{1t} is found to be useful in predicting the future values of another variable, Z_{2t} then Z_{1t} is said to Granger-cause Z_{2t};

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otherwise it fails to Granger-cause Z_{2t}. Conventionally, Z_{1t} fails to Granger-cause Z_{2t} if for all $s > 0$, the MSE of a forecast of $Z_{2,t+s}$ based on $\left(Z_{2,t}, Z_{2,t-1}, \cdots\right)$ is the same as the MSE of a forecast of $Z_{2,t+s}$ based on $\left(Z_{2,t}, Z_{2,t-1}, \cdots\right)$ and $\left(Z_{1,t}, Z_{1,t-1}, \cdots\right)$. Hence the MSE mathematically can be represented as:

$$MSE\left[\left(\hat{Z}_{2,t}(s)(1)\right)\right] = MSE\left[\left(\hat{Z}_{2,t}(s)(2)\right)\right]. \quad (3.4)$$

3.4.1 Testing for Granger Causality

As there are k-dimensional endogenous variables in the study, the hypothesis is stated for each of the k-series.

Hypothesis for Series 1:

H_0 : Live births do not influence maternal deaths.

H_1 : Live births influence maternal deaths.

Hypothesis for Series 2:

H_0 : Maternal deaths do not influence live births.

H_1 : Maternal deaths do not influence live births.

The test statistic associated with the Granger causality is given as follows:

$$F = \frac{\left[\left(ESS_R - ESS_U\right)/p\right]}{ESS_U/\left(T-2p-1\right)}, \quad (3.5)$$

`

where T is the number of observations in the sample, ESS_R = Error sum of squares (restricted) and ESS_U = Error sum of squares (unrestricted). The F statistic follows a χ^2, thus $F \sim \chi^2$.

It is worth noting that the null hypotheses in either case is rejected if $F > \chi^2_{(p)}$ at 5% significance level.

3.5 Vector Autoregressive with Exogenous Variable (VARX) Model

The VARX model is one of the most successful, flexible and easy to use models for the analysis of multivariate time series. This model became well-known in Chris Sims's article "Macroeconomics and Reality," (ECTA, 1980). It is an extension of univariate autoregressive process. Multivariate time series model with lag-length p is commonly used to find out the pairwise relationship between the different variables in a time series model. Generally, with $VAR(p)$ models, the first p lags of each variable in the system are used as regressors for each variable. *VAR* models are a special case of *ARMA* models. *VARMA* models for vector time series incorporate the *VAR* structure along with vector moving average terms for each variable. Yet, in a more general spectrum, these are a particular case of vector autoregressive with exogenous variable (*VARX*) models that allow for the addition of other regressors that are outside the system. The *VARX* model can be represented as follows:

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$$Z_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i Z_{t-i} + \sum_{i=0}^{s} \Lambda_i X_{t-i} + e_t, \quad (3.6)$$

where the output variables of interest, $Z_t = \left(Z_{1,t}, \cdots, Z_{k,t}\right)'$ is a (k x 1) matrix and can be influenced by other input variables, $X_t = \left(X_{1,t}, \cdots, X_{n,t}\right)'$ which are determined outside the model of interest. The variables Z_t are referred to as dependent (endogenous) variables, and the variables X_t are known as independent (exogenous) variables. The unobserved noise variables, $e_t = \left(e_{1,t}, \cdots, e_{k,t}\right)'$ are a (k x 1) vector white-noise process. Equation (3.8) can take polynomial form as:

$\Phi(B) Z_t = e_t$ and $\Phi(B) Z_t = \Lambda_t(B) X_t + e_t$ where $\Phi(B) = \mathrm{I}_k - \Phi_1 B - \cdots - \Phi_p B^p$ and $\Lambda(B) = \Lambda_0 - \Lambda_1 B - \cdots - \Lambda_s B^s$ are matrix polynomials in B in the backshift operator such that $B^i Z_t = Z_{t-i}$, the Φ_i is a $(k \times k)$ coefficient matrix, the Λ_i are a $k \times n$ matrix of exogenous variables and e_t are a (k x 1) sequence of multivariate white noise

The assumptions of the VAR model are:

1. $E(e_t) = 0, E(e_t e_t') = \Sigma_e$ which is positive definite and $E(e_t e_s) = 0$ for $s \neq t$

   .

2. For stability of the VAR process, the roots of $\det(\Phi B) = 0$ are on or outside the unit circle.

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3. The exogenous variables X_t are not correlated with residuals e_t, $E(X_t e_t) = 0$. The exogenous variables can be stochastic or non-stochastic (SAS/ETS 13.2 User's Guide, 2014).

3.6 Model Specification

By convention, identifying orders of the vector time series models is analogous to the method of identification for one-variate time series. For a set of observed vector series $Z_i, i = 1, 2, \cdots, T$, its underlying process can be identified from the pattern of sample correlation and partial correlation matrices after appropriate transformations are employed to obtain stationarity (Wei, 2006).

3.6.1 Stationarity Condition

The $VARX(p, s)$ model is fitted with stationary series that is, all components of the series must be stationary at level before fitting $VARX(p, s)$ model. If the series are not stationary, we difference the data to obtain stationarity. The ADF and KPSS tests were used to test the hypothesis that an observable time series is stationary with or without a unit root. This should be done for the variables separately.

3.6.2 Lag-Length Selection

The VARX model of equation (3.6) is very broad and can have many parameters in their structure. Given the *VARX* model of finite lengths $p = 1, 2, \cdots, P$ and

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$s = 1, 2, \cdots, S,$ the objective is to construct model that has as few parameters as possible that we need to estimate. They should also be able to appropriately represent the vibrant relationship existing between the multiple series (Tiao and Tsay, 1983).

Getting a precise lag-length *p* is very crucial because the addition of every further lag tend to reduce the needed parsimony in the model (Fackler Krieger, 1986). If the lag-length estimated is bigger than the eventual optimum model-length, which is considered to be over-fitting and have the tendency of producing inept parameter estimates (de Waele Broersen, 2003). On the other hand, if the selected model-order is smaller than eventual optimal model-order which may give imprecise forecasting values from the model

According to Williams and Brandt (2007), these guidelines can be helpful in selecting lag lengths especially for data that are collected monthly or quarterly.

i. The *VAR* models should usually have sufficient lags to incorporate the full cycle length of the data. Thus, in the case of monthly data, number of lags should be at least 12. For quarterly data the number of lags should be less than four.

ii. The lag-order should be at most a quarter of the degrees of freedom for one equation of the system. Information criteria would be used to select the number of lags to be included. The usual method is to fit $VAR(p)$ models with orders $p = 0, \cdots, p = \max$ and choose the value of p at which information criteria is minimum. All selection criteria are likelihood-based, and they comprise of two segments. The first part deals with the

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goodness-of-fit of the model to the data, while the second segment penalises more wasteful models. The goodness-of-fit of a model is often measured by the maximised likelihood. The three commonest information criteria are the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC) and Hannan-Quinn Information Criteria (HQ). The VAR models then are fitted with the appropriate lag lengths that arise. The information criteria are mathematically represented as follows:

$$AIC = \log\left|\hat{\Sigma}\right| + 2\hat{p}k^2 \big/ T, \tag{3.7}$$

$$BIC = \log\left|\hat{\Sigma}\right| + \hat{p}k^2 \log T \big/ T, \tag{3.8}$$

$$HQ = \log\left|\hat{\Sigma}\right| + \hat{p}k^2 \log\left(\log T\right) \big/ T, \tag{3.9}$$

where $\left|\hat{\Sigma}\right| = \det\left(1 \big/ T \sum_{t=1}^{T} \hat{e}_t \hat{e}_t' \right)$ is the determinant of the residual covariance with k being the number of variables, T is the sample size of the series and $\hat{p}$ being an estimate of p lag order.

3.7 Model Fitting

The k-dimensional $VARX\left(p, s\right)$ model as in Equation (3.6) can be estimated by the least squares (LS). Under the multivariate normality assumption that is for a k-dimensional normal distribution, the MS estimates of $VARX\left(p, s\right)$ model is asymptotically equivalent to the LS estimates. This study applied the LS estimation technique to estimate the unknown matrix coefficients

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$\left(\Phi_0, \Phi_1, \cdots, \Phi_p, \Lambda_0, \Lambda_1, \cdots, \Lambda_s \; and \; \Sigma_e\right)$ in Equation (3.6). The models *VARX* is stable if all the roots of $\left|\Phi Z_t\right| = 0$ lie on or outside the unit circle.

3.8 Diagnosis of the Fitted Model

Now that we have fitted the model to the vector time series data, we will next subject the fit to diagnostic test to find out if they do not infringe on any of the basic assumptions. Usually, these assessments are centred on the model residual analyses. The diagnostic checking is often carried out to verify whether the model residuals are consistent with multivariate white noise series. Multivariate white noise models are assumed to have zero-mean vector, invariant variance, and non-existence of serial correlation. They should also be independently identically multivariate normally distributed random variables. If the process $\{e_t\}$ is a vector of white noise series, then all the ACFs, PACFs and CCFs of the components should not be significantly different than zero. A fit is considered appropriate if it does not have or exhibit any significant autocorrelations nor cross-correlations in residual plots (Williams and Brandt, 2007). By convention, the fit is appropriate if the residual correlations lie between the two limits $\pm 2/\sqrt{T}$ (Newbold and Granger, 1986). Other statistical tools such as RSS, Durbin-Watson statistic, quantile-quantile plots, residual plots, Ljung-Box statistic, R^2 and the list goes on are also used to examine model fitness.

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3.8.1 Multivariate Ljung-Box Test

Portmanteau test was employed to check the presence or otherwise of serial correlations in the model residuals. The corresponding hypotheses test is as given below:

H_0 : The $VARX\left(p,s\right)$ model residuals are not serially correlated.

H_1 : The $VARX\left(p,s\right)$ model residuals are serially correlated.

To find out whether the model residuals are white noise, we employed the statistical hypothesis, and the Q-statistic as follows:

$$Q_{(h)} = T^2 \sum_{i=1}^{h} \left(T-i\right)^{-1} tr\left(\hat{\Gamma}_i' \hat{\Gamma}_0^{-1} \hat{\Gamma}_i \hat{\Gamma}_0^{-1}\right), \tag{3.10}$$

where $\hat{\Gamma}_i = \frac{1}{T-i} \sum_{t=i+1}^{T} \hat{e}_t e_{t-i}'$.

Then, the test statistic $Q_{(h)}$ is asymptotically distributed as a Chi-square distribution

with $Q_{(h)} = \left(h-p\right)k^2$ degrees of freedom. If the parameter coefficients are constrained, the $Q_{(h)}$ is then distributed as a χ^2 with degrees of freedom k^2h-b , and b denotes an unconstrained parameter estimated in the model (Box et al., 2008). For large values of the Q -statistic the study will reject the null hypothesis. It is worth noting that when the null hypothesis is rejected it does not essentially imply acceptance of the alternative hypothesis; it would rather mean adequacy of the fitted model (Reinsel, 1997).

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3.8.2 Multivariate ARCH-LM Test

Multivariate ARCH-LM test is used to determine the absence or otherwise of heteroscedasticity in the model residual series (Breusch, 1978). Suppose the residual vector series, $e_t = X_1 e_{t-1} + \cdots + X_m e_{t-m} + \upsilon_t$ where υ_t is a white noise vector series. It follows that multivariate ARCH-LM-test is based on the regression equation that follows:

$$\hat{e}_t = \Phi_0 + A_1 Z_{t-1} + \cdots + A_p Z_{t-p} + B_1 \hat{e}_{t-1} + \cdots + B_m \hat{e}_{t-m} + \varepsilon_t, \qquad (3.11)$$

where A_i and B_i are coefficient matrices and ε_t being the auxiliary regression residual vector. The hypothesis is stated as:

$$H_0 : B_1 = B_2 = \cdots = B_h = 0 \text{ (No ARCH effects)}$$

$$H_1 : B_i \neq 0 \text{ (ARCH effects exist).}$$

It is assumed that under H_o, $e_t = \upsilon_t$. The test statistic of the vector ARCH-LM is given as depicted below:

$$LM_h = T\hat{g}_h' \hat{\Sigma}_e^{-1} \hat{g}_h, \qquad (3.12)$$

where $g_h = (G_1, \cdots, G_h)'$ so that $G_h = T^{-1} \sum_{t=h+1}^{T} e_t e_{t-h}, \hat{\Sigma}_\varepsilon$ is the covariance matrix of the innovation process in equation (3.14). The decision rule is to reject the null hypothesis if the p-value of $\chi_h^2(\alpha)$ is less than the significance level α.

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3.9 Forecasting

The concept in respect of forecasting for the $VARX\left(p,s\right)$ model is like is that of vector $ARMA\left(p,q\right)$ model. Consider the $VARX\left(p,s\right)$ model given as:

$$Z_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i Z_{t-i} + \sum_{j=0}^{s} \mathbf{\Lambda}_j \mathbf{X}_{t-j} + e_t, \qquad (3.13)$$

where $\Phi_0 = \left(I - \Phi_1 - \Phi_2 - \cdots - \Phi_p\right)\mu.$

The components of the vector e_t are assumed to be mutually independent of each other (Box et al., 2008). In this regard taking conditional expectations of equation (3.13) from both sides and making use of the property that since the future white noise process $e_{t+h}, h>0$ is independent of the lagged and present values $Z_t, Z_{t-1}, \cdots,$ then the value of $E\left(e_{t+h}/Z_t, Z_{t-1}, \cdots,\right)$ is 0. The best predictor, in terms of minimum mean squared error, for $Z_{T+1/T}$ or 1−step forecast based on the available data at time T is as follows

$$Z_{T+1/T} = \hat{\Phi}_0 + \hat{\Phi}_1 Z_T + \cdots + \hat{\Phi}_p Z_{T-p+1} + \hat{\Lambda}_0 X_T + \hat{\Lambda}_1 X_{T-1} + \cdots + \hat{\Lambda}_s X_{T-s}, \qquad (3.14)$$

Forecasting for longer period, for example h-step forecast, can be attained by applying the chain rule of forecasting as depicted below:

$$Z_{T+h/T} = \hat{\Phi}_0 + \hat{\Phi}_1 Z_{T+h-1/T} + \cdots + \hat{\Phi}_p Z_{T+h-p/T} + \hat{\Lambda}_0 X_{T+h/T} + \hat{\Lambda}_1 X_{T+h-1/T} + \cdots + \hat{\Lambda}_s X_{T+h-s/T}. \qquad (3.15)$$

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3.10 Mean Absolute Percent Error (MAPE)

Mean Absolute Percent Error (MAPE) was applied to the forecasted values churned out by the two fitted models to enable us adjudge the fit with a better predictive accuracy. It simply means that the fit with the lower MAPE value from the predicted values will be considered more appropriate . The formula for MAPE can be found as:

$$MAPE = \frac{100\sum_{i=1}^{T}|Z_t - F_t|}{TZ_t}, \tag{3.16}$$

where T is the sample size, Z_t are the actual values and F_t are the forecasted values. The model is a good one for a value of $MAPE$ less or equal to 10%.

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CHAPTER FOUR

DATA ANALYSIS AND RESULTS

4.0 Introduction

This chapter discusses the analysis of the data. It closely looks for the connection between the time series variables and their lagged values. The preliminary analysis focused on summary statistics, level and trend of maternal deaths and live births over the study period. The chapter also contains further analysis on VARX modeling.

4.1 Preliminary Analysis

Table 4.1 shows the monthly maternal deaths, live births and maternal ages. The period under review recorded a total of 47,515 live babies that were successfully delivered while 250 maternal deaths were recorded at the UWRH. Also average of 22 women died annually while trying to bring forth new babies. On the other hand, an average of 4,132 babies were brought to life every year within the period under study. Table 4.1 also shows that the corresponding average monthly maternal deaths was approximately 2 over the period under review (January 2009 to June 2020). The results indicated that the mean age of women who visited the UWRH to deliver within the study period was 27 years with minimum and maximum ages as 17 and 40 years respectively. It was revealed that, all the variables found in Table 4.1 were positively skewed confirming distributional

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tails on the right found to fatter than on the left. The excess kurtosis associated with live births and maternal ages was that of a platykurtic distribution whilst maternal deaths was that of a leptokurtic distribution.

Table 4. 1: Descriptive Statistics of some Health Indicators

	Live Birth	Maternal Death	Maternal Age
Mean	344.3	1.8	27.0
Variance	8960.5	1.1	32.9
Kurtosis	-0.7	0.2	-0.5
Skewness	0.1	0.6	0.5
Minimum	155.0	0.0	17.0
Maximum	555.0	5.0	40.0
Sum	47515.0	250.0	3726.0

The plotted graph depicts the monthly measurements on maternal deaths spanning from January 2009 to June 2020. The plot as found in Figure 4.1 indicate that maternal death series shows no trend (pattern) but fluctuate slowly from 2009 through to mid-way 2020 amid intermittent flat trends. Also, the Maternal death series therefore seems to suggest some form of stationarity both in mean and in variance.

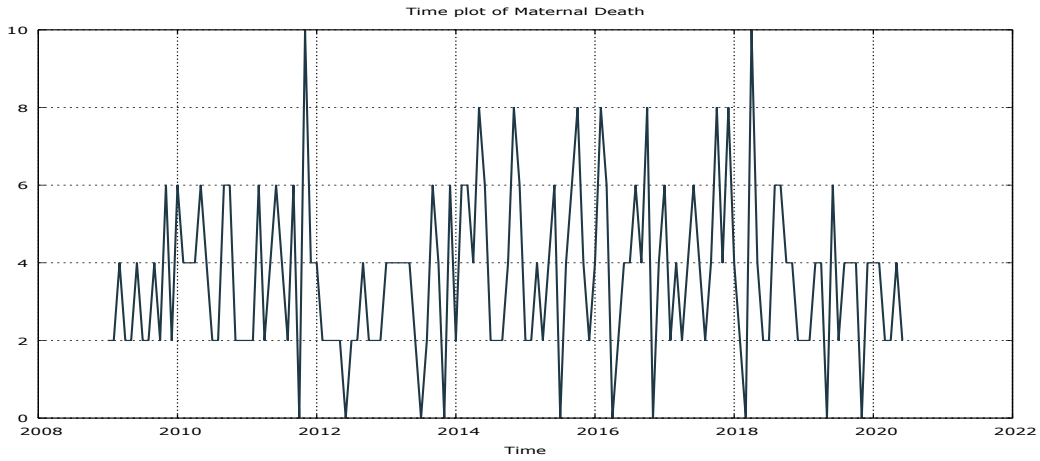

Figure 4.1: Time Plot of Maternal Death Series

Figure 4.2 displays the time series plot of the monthly maternal ages recorded in Wa Regional Hospital over the 138-month period. The pattern of maternal age demonstrates no discernible trends much like that of the maternal death series. The plot shows considerable variation in maternal ages over the years under review.

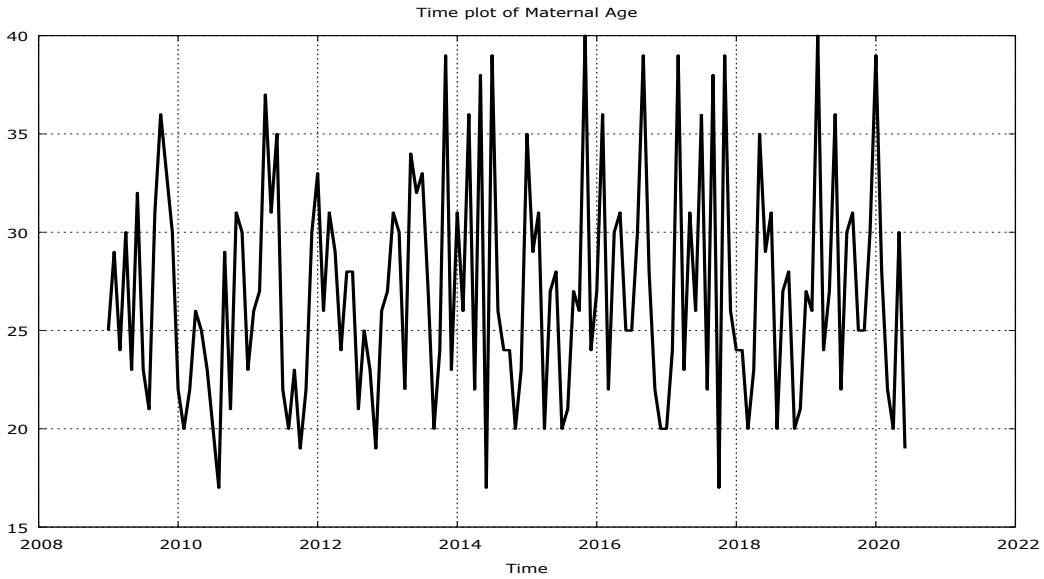

Figure 4.2: Time Plot of Maternal Age Series

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Figure 4.3 displays the time plot of monthly live births recorded in Wa Regional Hospital from January 2009 to June 2020. It was established from Figure 4.3 that live birth series over the period demonstrated an upward trend (pattern) from February 2009 to May 2015 with significant fluctuations around the non-constant mean and variability as it wanders along a virtual trend line. This trending (pattern) however looks weaker in the latter part of the period under review. The live birth series behaviour looks typical of a unit root nonstationary process.

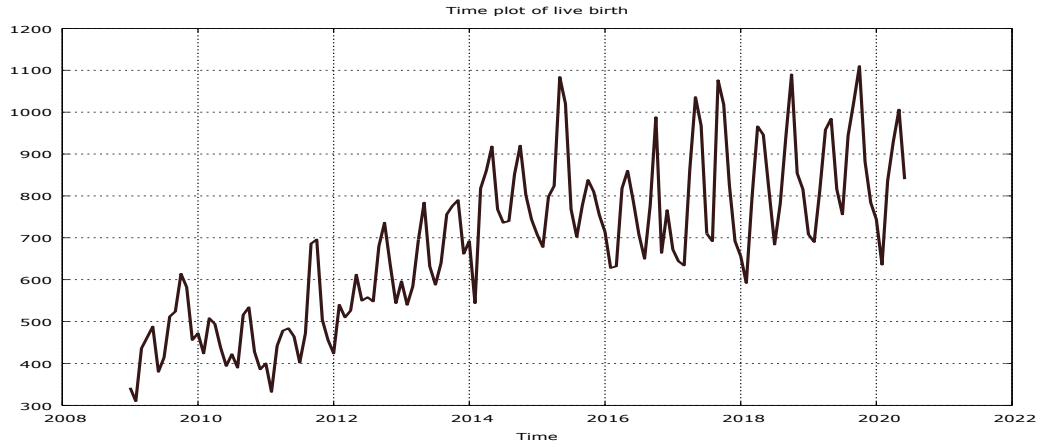

Figure 4.3: Time Plot of Live Birth Series

In addition, there exists a long-run equilibrium relationship between live births and maternal deaths.

4.3 Granger Causality Analysis

Test 4.3 tests the null hypothesis that maternal death is influenced only by itself and not by live birth. Also, test of the null hypothesis that live birth is influenced only by itself and not by the maternal death is captured in Table 4.3. From the results of the Granger causality tests, Table 4.3 demonstrates that from the results of Test 1 as found in Table 4.3, F-statistic (0.7316) and the p-value (0.5350)

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confirm that we cannot reject the null hypothesis. We deduce that the maternal death is influenced only by itself and not by live birth. For the second test, the F-statistic (1.3686) and the p-value (0.2554) suggest that we fail to reject the null hypothesis. We also conclude that live birth is only influenced by itself, not by maternal death. As a result, neither variable can have superior future values if the other variable's previous values are included.

Table 4.2: Granger Causality Test of Variables

Null Hypothesis	F-Statistic	p-value
Test 1		
Maternal Maternal Death does not Granger Cause Live Birth	0.7316	0.5350
Test 2		
Live Birth does not Granger Cause Maternal Death	1.3685	0.2550

4.4 VARX Model Fitting

The model fitting approach was adopted in this study along with several tests in other to pave way to make an informed decision on the choice of model that best fit the observed series.

4.4.1 Test for Stationarity of Time Series Data

The $VARX\left(p,s\right)$ model can only be valid and well-founded if it is fitted with stationary series. That is to say that all the time series must contemporaneously be stationary. The trend condition in Figure 4.1 and Figure 4.2 seems to be suggesting that the two series plots are stationary at levels and do not need to be

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coerced to obtain stationarity. However, the time plot in Figure 4.3 exhibits an upward trend behaviour which is the characteristics of a non-stationary series. The results from Table 4.4 indicate that the ADF test statistics of -10.0834 and the KPSS test statistic of 0.1980 in absolute terms were all greater than the critical values of 2.9300 and 0.4650 respectively at the 5% level suggesting that the assumption of stationarity have been met after differencing the live birth series unlike the before differenced series. Also, after differencing the maternal deaths series as found in Table 4.4 confirm that the statistics for ADF and KPSS (-11.408 and 0.0330) in absolute terms to be greater than the 5% critical values (-2.9300 and 0.4650) respectively to be stationary as compared to the before differenced series. Therefore, we can model that the data to be stationary at the after differencing hence can be considered as levels applications.

Table 4.3: Stationarity Tests for Maternal Death and Live Birth

Variable		**Before Differencing**	**After Differencing**	
	Test Type	**t-statistic**	**t-statistic**	**5% Critical value**
Live Birth	ADF	-2.1720	-10.0834	2.9300
	KPSS	2.4436	0.1980	0.4650
Maternal Death	ADF	-11.8940	-11.4080	-2.9300
	KPSS	0.1980	0.0330	0.4650

The number of lags for the VARX model was chosen based on information criteria. $VARX(p,s)$ model. The rule of thump is to fit $VAR(p,s)$ models with order $p=0,\cdots,p=\max,s=0,\cdots,s$ and select the p and s values at which the

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information criteria is minimum. In this regard the AIC, BIC and HQ of Table 4.5, selected pairs of values as given below: $AIC:(p,s)=(13,1)$; $BIC:(p,s)=(4,0)$; $HQ:(p,s)=(5,1)$. Thus, the information criteria suggested three different candidate models that is $VARX(13,1)$, $VARX(4,0)$ and $VARX(5,1)$ with max p and max s set at 13 and 2 respectively (p is AR order and s is order of the exogenous variable).

Table 4.4: Selection of Candidate VARX Models

Candidate Models	AIC	BIC	HQ
VARX (4,0)	13.8160	**14.2072***	13.9750
VARX (5,1)	13.7146	14.2387	**13.9276***
VARX (13,1)	**13.5444***	14.8180	14.0618

From Table 4.5, it is obvious that no model was unanimously selected by the three information criteria. In this regard, the least value among the asterisked information criteria's were used to decide on the model retention. In view of this, the $VARX(13,1)$ model was adjudged as the optimal model. Hence the $VARX(13,1)$ model being refined following the fact that some model parameters were not significant and as a result dropped can be stated as below:

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$$\hat{Z}_t = \begin{pmatrix} -0.46 & 0 \\ 0 & -0.92 \end{pmatrix}\hat{Z}_{t-1} - \begin{pmatrix} 0.38 & 0 \\ 0 & 0.86 \end{pmatrix}\hat{Z}_{t-2} - \begin{pmatrix} 0.43 & 0 \\ 0 & 0.85 \end{pmatrix}\hat{Z}_{t-3} - \begin{pmatrix} 0.28 & 0 \\ 0 & 0.60 \end{pmatrix}\hat{Z}_{t-4} - \begin{pmatrix} 0.29 & 0 \\ 0 & 0.34 \end{pmatrix}\hat{Z}_{t-5} - \begin{pmatrix} 0.24 & 0 \\ 0 & 0.15 \end{pmatrix}\hat{Z}_{t-6} - \begin{pmatrix} 0.22 & 0 \\ 0 & 0.09 \end{pmatrix}\hat{Z}_{t-7} - \begin{pmatrix} 0.18 & 0 \\ 0 & 0 \end{pmatrix}\hat{Z}_{t-8} - \begin{pmatrix} 0.29 & 0 \\ 0 & 0 \end{pmatrix}\hat{Z}_{t-9} - \begin{pmatrix} 0.34 & 2.94 \\ 0 & 0 \end{pmatrix}\hat{Z}_{t-10} + \begin{pmatrix} 0.29 & 0 \\ 0 & 0 \end{pmatrix}\hat{Z}_{t-12} + \begin{pmatrix} 0.21 & 0 \\ 0 & 0 \end{pmatrix}\hat{Z}_{t-13} + \begin{pmatrix} 0 \\ 0.02 \end{pmatrix}\hat{X}_{t-1} + e_t \tag{3.17}$$

with $\Sigma_e = \begin{pmatrix} 1366.97 & 4.67 \\ 4.67 & 1.20 \end{pmatrix}$.

4.6 Model Adequacy Checks

In vector time series analysis, choosing the suitable model to the observed series data is expressly linked to the residual analysis of the model. The basic assumption of multivariate time series modeling is that, for a model to be deemed optimal, the model residual series must behave like multivariate white noise series. That is, the residuals are independently and identically distributed with zero mean, variance that is constant, and they are serially uncorrelated. In this wise, this takes critical look at the following graphs and test output from the fit.

Figure 4.4 shows the time plot of the standardized residuals from the $VARX\,(13,1)$ model fitted to live birth and maternal death series. The parameters were estimated using ordinary least squares. These plots tend to support the model as no trends are discernible which finds the model adequate.

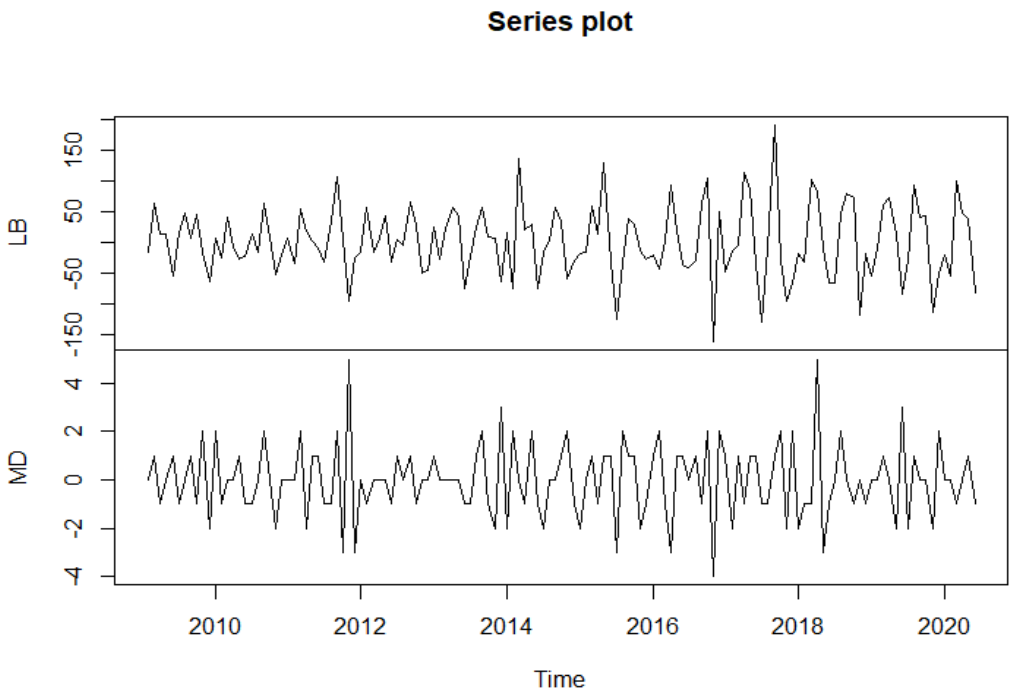

Figure 4.4: Residual Time Plot of Live Birth and Maternal Death

The residual cross correlation of live births and maternal deaths as displayed in Figure 4.5 showed no spike outside the confidence bands which portray that the model residuals do not show any autocorrelations at higher lag orders. This means that the residuals of the live births and maternal deaths are not cross correlated and hence the model can be deemed adequate.

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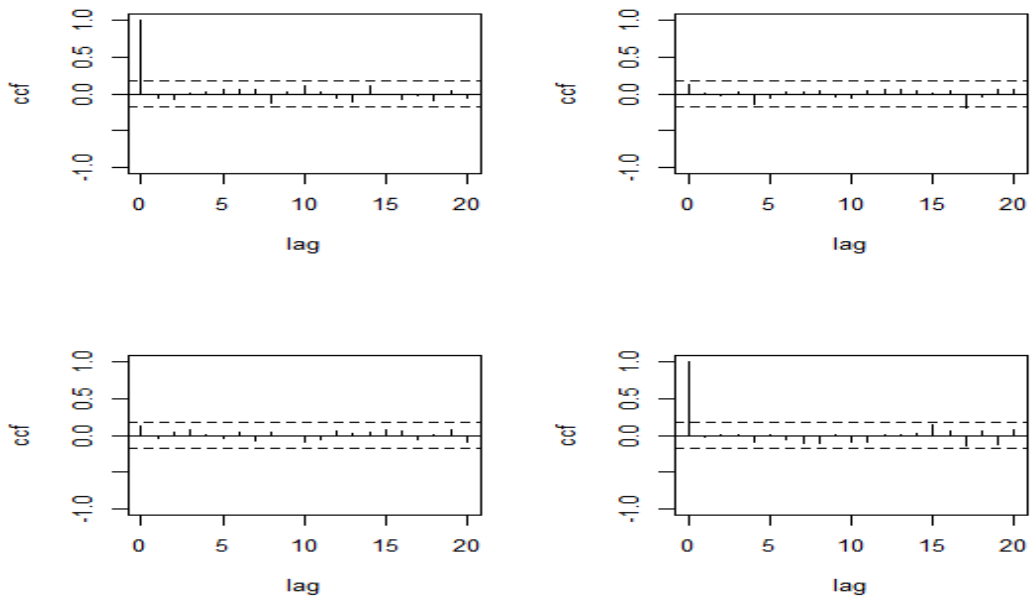

Figure 4.5: Residual Cross-Correlations of Live Birth and Maternal Death

The p-values of the Ljung-Box test statistic were well above the alpha (α) value of 0.05 in Figure 4.6, suggesting that the residual series of the model do not depart from a white noise process and hence the VARX (13,1) model is appropriate.

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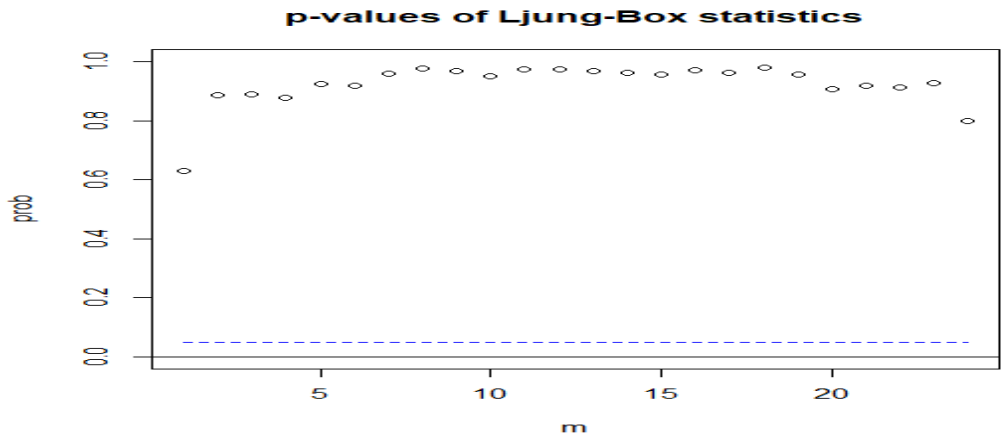

Figure 4.6 Multivariate p-values of Ljung Box Statistics

The sample autocorrelations and cross-correlations of residuals from the model are shown in Figure 4.7. All autocorrelations and cross-correlations are encapsulated within the -2 or 2 standard errors, which are very close to zero but not entirely. As a result, we can infer that there is no statistically significant evidence of nonzero residual autocorrelations in the plot.

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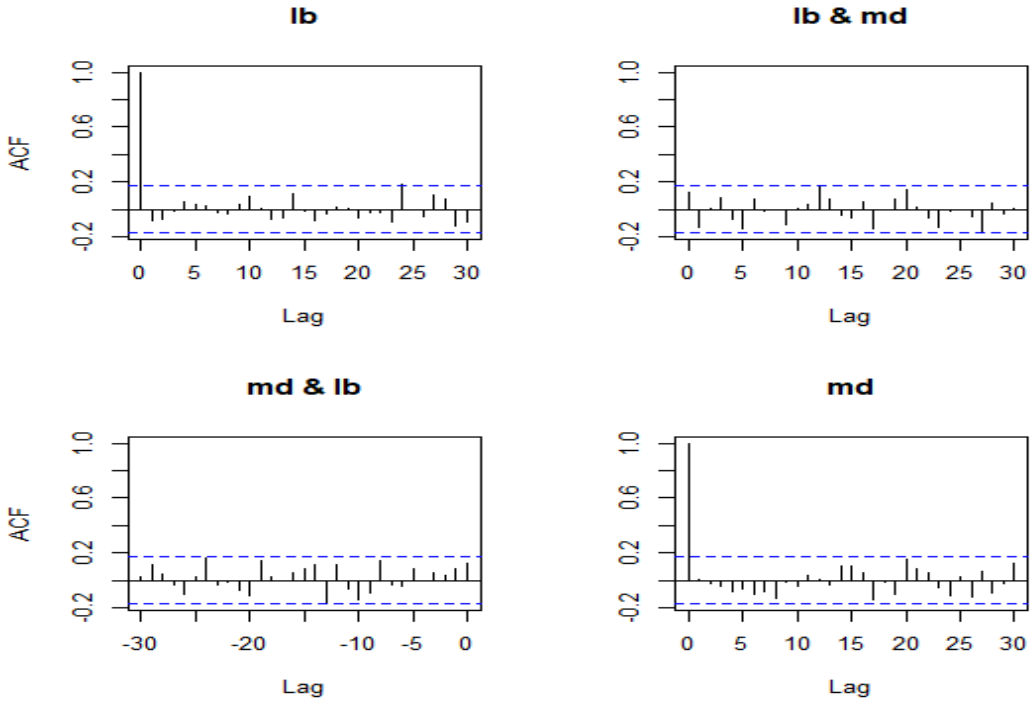

Figure 4.7: Residual Autocorrelations and Cross Correlations

The multivariate test of normality was also assessed using the Jarque-Bera test and Shapiro Wilks test as shown in Table 4.5. The Jarque-Bera test statistic with $p-value=0.2271$ indicates that the residuals are normal since the $p-value$ is greater than the 5% significant level. Also, the Shapiro Wilks test confirmed the normalcy of the residuals with a $p-value$ of 0.5258 which is also greater than the 5% significant level. In both cases, we fail to reject the null hypothesis and conclude that the residual series is normal.

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Table 4.5 Assessing the Multivariate Normality of the Model

Test Type	Test Statistic	df	P-value
Jarque-Bera	5.4170	4	0.2271
Shapiro Wilks	0.9902	-	0.5258

The ARCH-LM test in Table 4.7 indicates that there is clearly no evidence of heteroscedasticity in the model residuals since the p-values are all greater than the alpha (α) value of .05. This makes the model adequate for predictions.

Table 4.6: ARCH-LM Test of Residuals from VARX (13, 1) Model

Lag	Test Statistic	df	p-value
12	6.2260	12	0.9040
24	19.1950	24	0.7420
36	31.0520	36	0.7030
48	38.9380	48	0.8220

As can be seen from Figure 4.8, the blue dots represent roots of the characteristics polynomial and also known as the inverse roots are all inside the unit circle (unit diameter). In other words, the roots are less than one in moduli, which implies that our VARX (13, 1) model is stable. Given adequate initial values, it can be used to generate stationary time series with constant means, variances, and covariance structure.

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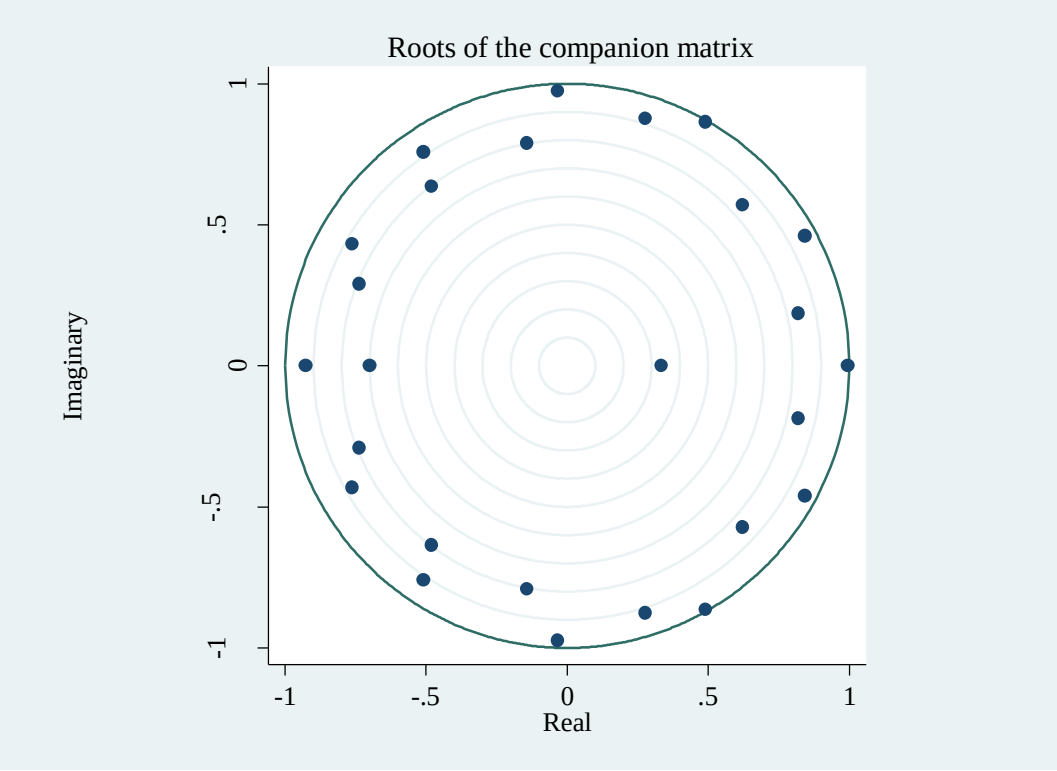

Figure 4.8: Roots of the Characteristic Polynomial

After passing through the goodness-of-fit-test, we then employed the estimated VARX (13, 1) model to forecast live births and maternal deaths for the period July 2020 to May 2021 and the forecasted values matched the observed ones to ascertain the forecast accuracy of the fit. From Table 4.8, it would be noticed that the actual values and that of the predicted ones are not far from each other for both live birth and maternal death cases. For instance, if we look at the live birth actual value (547.234) and its predicted value (546.526) for the month of October, they are very close. Also, both the actual and predicted values of the data find no value falling outside the 95% confidence interval and hence an indication therefore that the VARX (13, 1) model is adequate for use in the monthly forecast of live birth and maternal death cases at the UWRH.

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Table 4.7: VARX (13, 1) Forecasting Outcomes

Variable	Month	Actual value	Predicted value	95% Confidence Interval	
				Lower Limit	Upper Limit
Live Birth	Jul. 2020	408.4450	367.8510	214.0160	521.6860
	Aug. 2020	487.6720	555.2260	386.9570	723.4940
	Sep. 2020	547.2340	629.2610	457.6650	800.8560
	Oct. 2020	547.2340	546.5260	370.3340	714.5980
	Nov. 2020	474.4330	427.4430	253.8400	601.0460
	Dec. 2020	439.5820	384.0000	208.2670	559.7340
	Jan. 2021	546.2340	630.2610	457.6650	800.8560
	Feb. 2021	550.2330	546.5260	340.3340	710.5980
	Mar. 2021	587.6720	535.2260	384.9570	724.4940
	Apr. 2021	460.4450	378.8510	21.0160	531.6860
	May 2021	465.434	427.4530	254.8410	603.0460
Maternal Death	Jul. 2020	0.7230	0.9320	-3.4140	5.2790
	Aug. 2020	2.1500	2.0650	-3.0430	7.1740
	Sep. 2020	1.9090	1.9100	-3.3440	6.9660
	Oct. 2020	2.3170	2.5730	-2.5960	7.7420
	Nov. 2020	2.1230	2.3200	-2.8810	7.5210
	Dec. 2020	2.1460	2.3630	2.6840	7.6000
	Jan. 2021	1.1340	1.7230	-1.5140	5.3090
	Feb. 2021	1.5320	2.0650	-2.0430	7.1040
	Mar. 2021	1.5110	2.0650	-3.0430	7.1340
	Apr. 2021	2.3120	2.5730	-2.5700	7.9420
	May 2021	2.1500	2.3630	- 2.7840	7.4100

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CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

In this chapter, we present summary of the study findings, conclusions and recommendations. The study data were obtained from the registers of the Gynaecology and Obstetrics Unit of the UWRH for the period January 2009 to June 2020. The study data included two endogenous variables (LB and MD) and one exogenous variable (MA).

5.1 Summary

The study primarily was on modelling and forecasting maternal mortality and live births in the UWRH through the application of VARX models. The data for the entire period of study covered a total 138 months (January 2009 to June 2020). According to the findings of this study, a total of 47,515 expectant mothers delivered live babies at the UWRH, however 250 of these mothers died during pregnancy, childbirth, or during the first six weeks after giving birth.. This statistic revealed above yielded a total of 526.2 maternal deaths per 100,000 live births during the period under review (January 2009 to June 2020).

The distortion from that of the normal distribution confirmed a positive skewed distribution for the variables under study however, whilst the distributional shape of the maternal deaths was leptokurtic that of live births and maternal ages respectively exhibited a distributional shape which is platykurtic.

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The trend (pattern) from the time series plots revealed no particular trend in the maternal deaths and maternal age series respectively however an upward trend was realised from the live birth's series.

The findings further showed that the endogenous variables (LB and MD) do not Granger Cause each other. It simply means that on one hand, LB does not need the past values of MD to improve it forecasts. The reverse is also true. On the other hand, the two variables would rather perform as independent univariate framework rather than when put together. Other analysis in the study has also indicated that LB and MD have one cointegrating relationship. It means that there is a long-run equilibrium relationship between LB, and MD. VARX (13, 1) model was adjudged the most suitable model for forecasting future LB and MD at the UWRH. This model met all assumptions and diagnostic tests of a good VARX model.

After being confirmed as the most suitable fit for the data, the VARX (13, 1) model was then used to predict LB and MD for the next six months. The predicted values were compared with the observed values and the differences indeed between the observed and forecasted values spectacularly was very little. The findings further revealed that both observed and predicted values fall within the confidence interval. Therefore, we could conclude that VARX (13, 1) model is suitable for use to forecast monthly LB and MD at the UWRH.**5.**

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5.2 Conclusions

VARX (13, 1) model was selected as the most adequate model for predicting future LB and MD cases for the Wa Regional Hospital

According to the findings, a total of 47,515 expectant mothers delivered live babies at the UWRH, however 250 of these mothers died during pregnancy, childbirth, or during the first six weeks after giving birth.. These statistics yielded a total of 526.2 maternal deaths per 100,000 live births during the period under review.

The study also indicates that Live birth exhibits an increasing trend patterns, while Maternal death and Maternal age reman patternless over the study period (January 2009 to June2020).

The findings further show that the endogenous variables (live birth and maternal death) do not Granger Cause each other implying that live birth and maternal death are non-causal, thus neither needs the other's past values for better predictions. They are therefore said to be independent. On the other hand, the two variables would rather perform as independent univariate framework rather than when put together.

After being confirmed as the most suitable fit for the data, the VARX (13, 1) model was then used to predict LB and MD for the next twelve months. The predicted values were compared with the observed values and the differences indeed between the observed and forecasted values spectacularly was very little.

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The findings further revealed that both observed and predicted values fall within the confidence interval. Therefore, we could conclude that VARX (13, 1) model is suitable for use to forecast monthly LB and MD at the UWRH.

. In addition, the predicted values of LB and MD from the VARX (13, 1) model tend to mimic with that of the actual values.

5.3 Recommendations

The following are recommended for policy makers and stakeholders

1. The trend of maternal mortality is observably steady, yet the maternal death values are generally high and resulting from well-known factors. The Regional Health Management Teams as well as private stakeholders are encouraged to increase collaboration and prioritise more resources to disseminate information on early registration and continual attendance to ANC for early detection and prompt checking.
2. Further studies should consider applying more parsimonious models other than VARs, VARMA among others to study live births, baby weight and maternal deaths.
3. Further research on live births and maternal deaths should be conducted in a univariate framework. Since the findings revealed that live births and maternal deaths would rather perform better as independent variables.

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APPENDICES

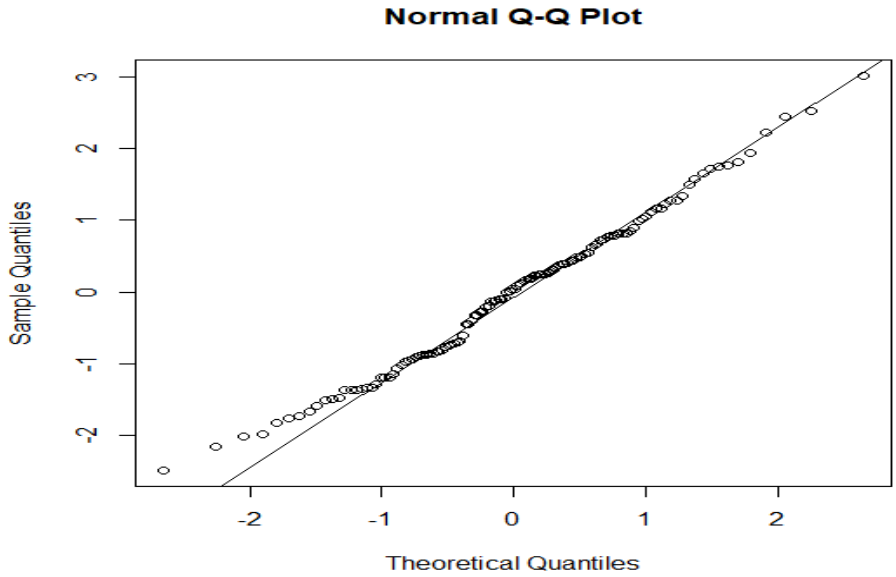

Figure A1: Normal Q-Q Plot

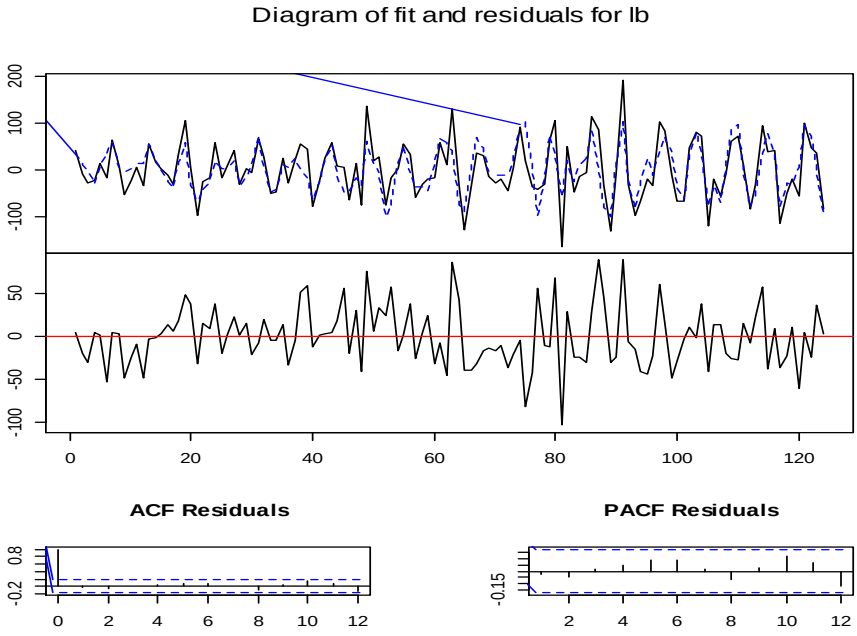

Figure A2: Plots of Fitted and Residuals for Live Birth

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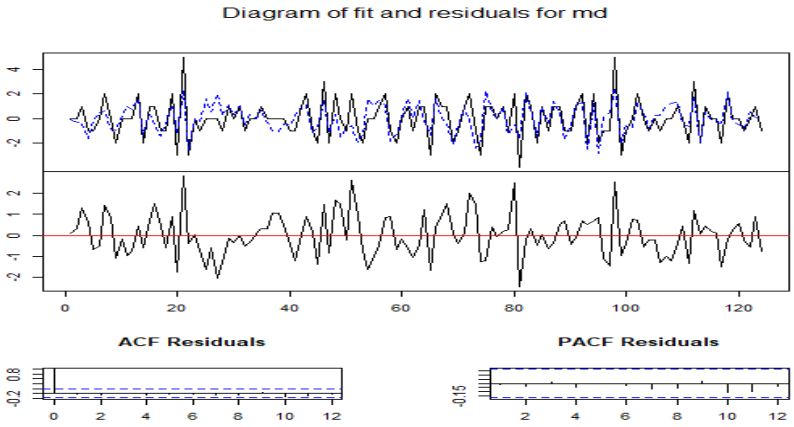

Figure A3: Plots of Fitted and Residuals for Maternal Death

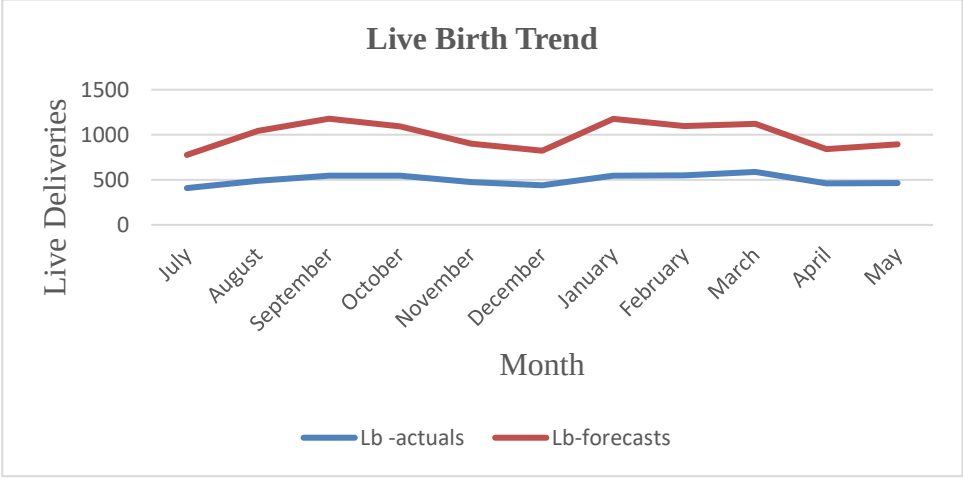

Figure A4: Line and Forecast Plots of Live Births

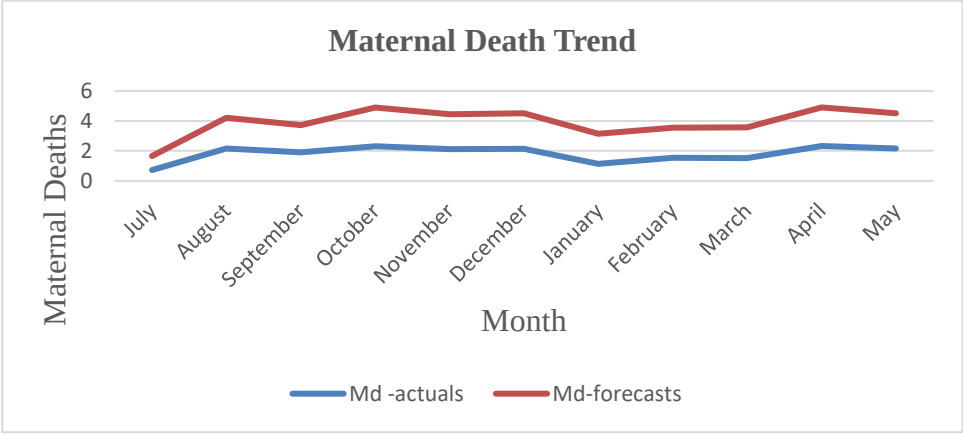

Figure A5: Line and Forecast Plots of Maternal Death