BINDURA UNIVERSITY OF SCIENCE EDUCATION

DEPARTMENT OF MATHEMATICS AND PHYSICS

FACULTY OF SCIENCE AND ENGINEERING

TIME SERIES ANALYSIS OF MATERNAL MORTALITY: A CASE STUDY OF BINDURA PROVINCIAL HOSPITAL, ZIMBABWE.

A RESEARCH SUBMITTED BY:

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TO

THE FACULTY OF SCIENCE AND ENGINEERING.

BINDURA UNIVERSITY OF SCIENCE EDUCATION.

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT OF THE BACHELOR OF SCIENCE HONORS DEGREE IN STATISTICS AND FINANCIAL MATHEMATICS (HBScSFM)

SUPERVISOR: MS J PAGAN'A

DECEMBER 2022

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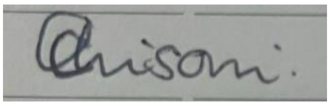

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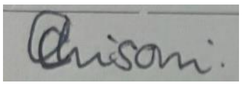

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DEDICATION

I dedicate this dissertation to my parents, Mr M. Chisoni and Mrs S. P. Chisoni, my brother Dumisani Chisoni and my husband Mr T. Matangira, who have made huge sacrifices towards my schoolwork.

ACKNOWLEDGEMENTS

My first acknowledgement goes to my supervisor, Ms J. Pagan'a for her academic support, who by her commitment and patience contributed to the successful compilation of this project. My gratitude also goes to my lecturers, Bindura University Statistics and Mathematics department and my fellow students for their support and assistance during my studies. It will be a gross miscarriage of justice if I cannot acknowledge my family their support both financially and non-financially, and also not forgetting Mr O. Ngorima who helped me a lot throughout the compilation of this research project.

Above all foremost, profound gratitude goes to the ALMIGHTY GOD, KING OF KINGS who gave me the strength, vision and ability to execute my plans and endeavours during my research report and led me all the way during the course of my studies.

ABSTRACT

This study's main thrust was on the time series analysis of maternal mortality at Bindura Provincial Hospital from period of year 2010 to year 2020 with the aim of building the best fit time series model to forecast maternal mortality for the next 5 years. The researcher collected secondary data from Bindura Provincial Hospital, Health Information Department. The data provided was for the total live births and maternal mortality recorded at the hospital from the year 2010 to year 2020. The researcher employed the descriptive research design, using the Box- Jerkins Test in building the model. Data was analysed using EViews 12 and ARIMA (1, 1, 1) came out to be the best fit time series model to forecast the yearly maternal mortality for the next 5 years. The best model was ascertained by comparing the various model selection criterion and the diagnostic tests for various models and the Akaike Information Criterion with the least value was selected. The forecasting results indicate that the Bindura Provincial Hospital needs to adopt the forecasting method to forecast their data. The observed results showed a decreasing trend, and the forecasted data displayed a constant trend with slight changes in overall decreasing slope for preceding five years. Bindura Provincial Hospital Officials need to adapt technologically advanced methods of data storage and do away with paperwork to reduce data losses. Furthermore, researchers should consider carrying out a qualitative research design using key information through interviews with stakeholders, staff members that seek to answer the reasons behind the experienced trend.

Keywords: *Time series analysis, ARIMA model, Maternal mortality forecasting*

Table of Contents

LIST OF TABLES

LIST OF FIGURES

ACRONYMS

ACF	Autocorrelation Function
ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average

BUSE	Bindura University of Science Education
MMR	Maternal Mortality Ratio
BPH	Bindura Provincial Hospital
MA	Moving Average
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
PACF	Partial Autocorrelation Function
RMSE	Root Mean Square Error
SARIMA	Seasonal Autoregressive Integrated Moving Average
SIC	Schwarz Criterion
SPSS	Statistical Package for Social Science
VIF	Variance Inflation Factor
WHO	World Health Organization

CHAPTER 1

INTRODUCTION OF THE STUDY

1.0 Introduction

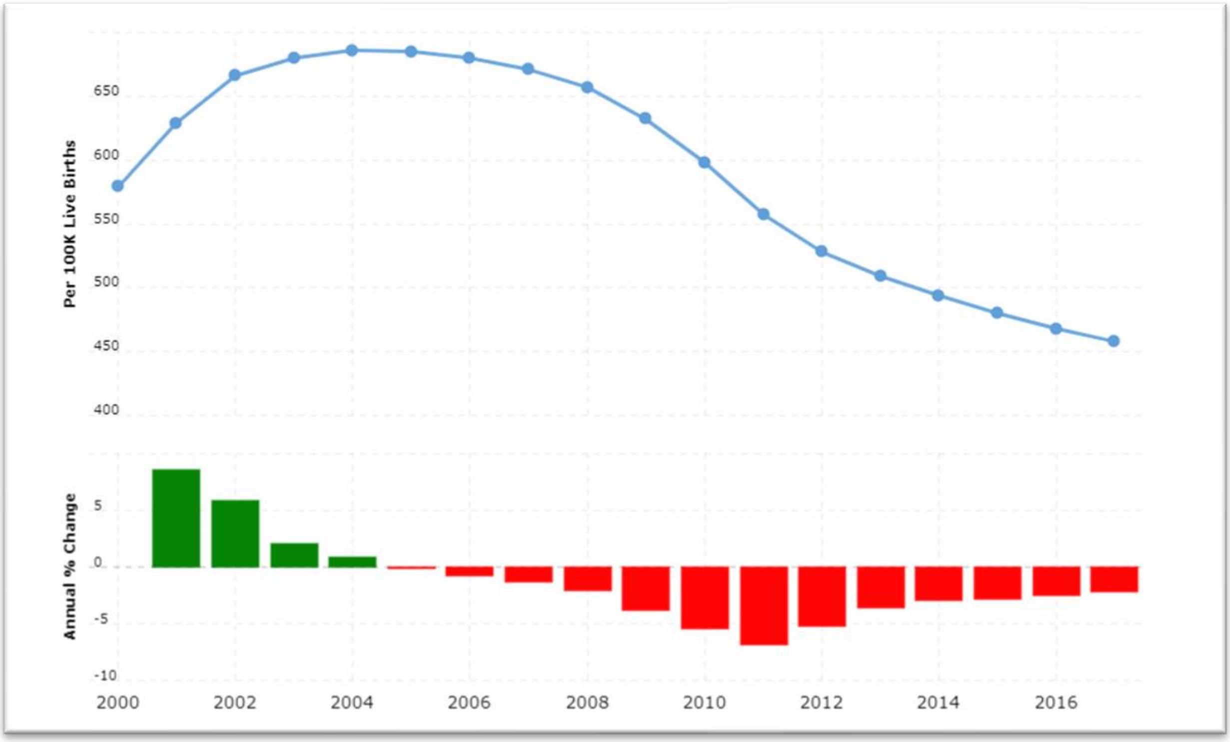
Maternal mortality is a loss of human life, and it affects those left behind and at times the baby may survive, posing a great challenge. It is imperative for any government to have means and ways of minimizing maternal mortality at all costs since the future rest on new and young generations. Zimbabwe made some effort to try and minimize maternal mortality since independence, but whether maternal mortality has decreased at Bindura Hospital during the selected period is a matter the researcher wants to unravel by doing a time series of maternal mortality at this provincial hospital.

1.1 Background

Approximately 810 women per day in 2017 died from premature deaths associated to pregnancy and delivery (World Health Organization (WHO), 2019). Maternal mortality refers to deaths that are caused by pregnancy or childbirth problems. This ongoing worldwide issue is addressed by Sustainable Development Goal (SDG) 3, which intends to "guarantee good health and encourage the well-being for people at all ages." Then, to meet SDG Target 3.1, which is to lower the global (MMR) to less than 70 per 100,000 live births by 2030, the methods developed by WHO and its allies to eradicate severe maternal mortality are put into implementation. The MMR counts the number of pregnant women who die during their pregnancy or within 42 days of giving birth for every 100,000 live births.

According to WHO (2017), maternal mortality in developed countries appears to be at a lower level as compared to developing countries like Zimbabwe. Zimbabwe ranked within top 20 countries with high maternal mortality rates in the world with **458 per 100,000 births as at 2017 Zimbabwe MMR rates.** Experts attributed 18 percent of these deaths to unsafe abortions. Zimbabwe was ranked number on number 18 globally. Expecting mothers are expected to deliver at home or at their shrines or place of worship. Being impoverished may also prevent some expecting mothers from going to the hospital since they may not be able to afford the expenses. High rates of maternal mortality may come from some pregnant women not going to the hospitals due to poverty and illiteracy. A pregnant women is expected to give birth at home, at a shrine, or in a place of worship because they believe the Almighty will help them. In some instances, expecting mothers only visit hospitals after a complication, which at times will be too late. The figure below illustrates Zimbabwe MMR trends.

Figure 1.1 Zimbabwe Maternal Mortality Rate 2000- 2017



Source: Extracted from Macrotrends (2022)

Zimbabwe Ministry of Health report (2019) cited by Ngorima (2022) states that MM caused almost a third of all fatalities among women who were of reproductive age. In countries like Ethiopia, where maternal deaths are the top epidemic for women of reproductive age, Meh (2019) hypothesizes that less than half of the total women population attend one antenatal appointment. While the initial antenatal check-up may be free in some countries, women are obliged to pay for any additional appointments due to the poor quality of care offered there, which may become burdensome for some families and some mothers who may be single with no other means of upkeep (Ezeh, 2014).

A 2018 report on maternal mortality from the WHO, UNICEF, World Bank Group, and United Nations Population Division predicted 295 000 maternal deaths globally in 2017. This data showed a 38% decrease since the year 2000, or a decrease of little under 3% annually. At UN Millennium Summit (2000), reducing maternal mortality was chosen as one of the eight Millennium Development Goals by current governments (MDGs). The summit aim was to enhance maternal health by lowering the MMR by 75% by that year, which was designated as MDG 5. Many African countries have reduced their MMR by more than half, including Rwanda (79%), Mongolia (71%), Er, Zambia (60%) and Cabo (51%). According to WHO, enhancing maternal health continues to be one of their top goals. Urgent efforts and increased political support for women and children are required to reach the MDG aim of lowering maternal mortality by 70%. A further factor in reaching MDG 4 of lowering child mortality is enhancing maternal health (UN, 2014; Asia, 2013).

1.2 Problem Statement

Maternal mortality remains high globally despite the commitment made in the MDGs (Klobodu et al, 2018). According to WHO (2015) cited by Machira (2017), maternal health is still a problem for public health in developing nations, particularly in SADC region. Zimbabwe's maternal mortality rate is still alarmingly high (Mlambo et al, 2013). With 462 maternal deaths per 100,000 live births, Zimbabwe is one of the top 40 high maternal mortality countries in the world (WHO, 2021). Zimbabwe currently has big hospitals such as Parirenyatya Hospital, Harare, General Hospital, Chitungiwza General Hospital, and several provincial hospitals. Clinics and private hospitals are also available in Zimbabwe and due to the availability of these healthy institutions one would conclude that health is now in the reach of many Zimbabweans. In the same sense, maternal rate is expected to be very low but, however WHO (2019) report, indicated that maternal death could still be high in Zimbabwe as the country is ranked position 18 globally. There is still a significant high rate of maternal mortality despite proliferation of hospitals in Zimbabwe. Time series trends analysis on maternal mortality in Zimbabwe has been a grey area in existing Zimbabwe literature. The ministry of health in Zimbabwe relies on these statistics for decision making and enhancing healthcare system. Research on MMR pattern and forecasting is a useful starting point. Most researchers in the literature under review used descriptive and odd ratio methods for analysis, which are limited to their data and cannot be extended to make predictions about future trends.

1.3 Research Objectives

- To analyse the maternal mortality trends at Bindura Hospital between year 2010 and 2020.
- To forecast the maternal mortality at Bindura Hospital between 2021 and 2025.

- To determine the relationship between maternal mortality and communicable diseases, Aids & TB, Unknown Diseases, and socio-economic status

1.4 Hypothesis

- There is a statistically positive significant relationship between maternal mortality and socioeconomic status, diseases, and education level.
- There is a statistically significant high maternal deaths at Bindura Hospital during the period 2010 and 2020.
- There will be is a statistically significant high maternal deaths at Bindura Hospital between 2021 and 2025.

1.5 Significance of the study

1.5.1 to researcher

This study is a requirement in partial fulfilment of the researcher's degree programme. It will also improve intellectual capabilities and enhance the researcher's research skills for the purposes of employment. Besides this, the researcher will also be able to assist other researchers because of the skills developed during working up this research.

1.5.2 to the university

The study will advance our understanding of the gray area in Zimbabwean literature and lay the groundwork for later studies. The research shall be made available to Bindura University of Science Education's library for academic purposes.

1.5.3 to the community

The study will help elevate women knowledge on maternal health thereby impacting maternal mortality free society including a healthy populace which may translate into a better standard of living for the community.

1.5.4 to the ministry of health

This study will enhance maternal health policy making and highlighting critical on maternal mortality that have been ignored in Zimbabwe.

1.6 Assumptions

Since the hospital records and hospital respondents will be used, the researcher held the following assumptions: information that will be supplied by the hospital records and staff members will be credible.

1.7 Delimitation

The study seeks to assess Maternal Mortality at Bindura Provincial Hospital in Mashonaland Central Province and is confined to a period between 2010 to 2020.

1.8 Limitations

The study was limited by some reluctance by some officers to release information due to the nature of the confidential nature of health records. This was countered by the fact that the researcher will indicate to the authorities that the study would is only for academic purposes and great care will be exercised to maintain the information in confidentiality.

1.9 Definition of key terms

1.9.1 Maternal Mortality: - refers to a woman dying from pregnancy-related reasons either during her pregnancy or within the first 42 days of her pregnancy. It is shown as a ratio to the population's 100,000 live births. (World Health Organization, 2004).

1.9.2 Time series: is a collection of observations made over a specific period or a graph showing a succession of data points ordered according to time. A time series is often a sequence captured at several evenly spaced moments in time.

1.10 Summary of the chapter

This study sought to understand maternal mortality as it has become an issue of major concern in Zimbabwe and the entire globe. The researcher believes that with enough research and analysis, it is very possible to reduce maternal mortality. The study's findings may benefit a variety of organizations, including clinics, hospitals, and other institutions. There are then four more chapters. The literature on maternal mortality is thoroughly reviewed in Chapter 2. The research design and particulars of the study's execution are subjects covered in Chapter 3. The latter chapters concentrate on the actual research that was done for this project. The study findings are presented in chapter 4, and a discussion of the results is presented in chapter 5.

CHAPTER 2

REVIEW OF RELATED LITERATURE

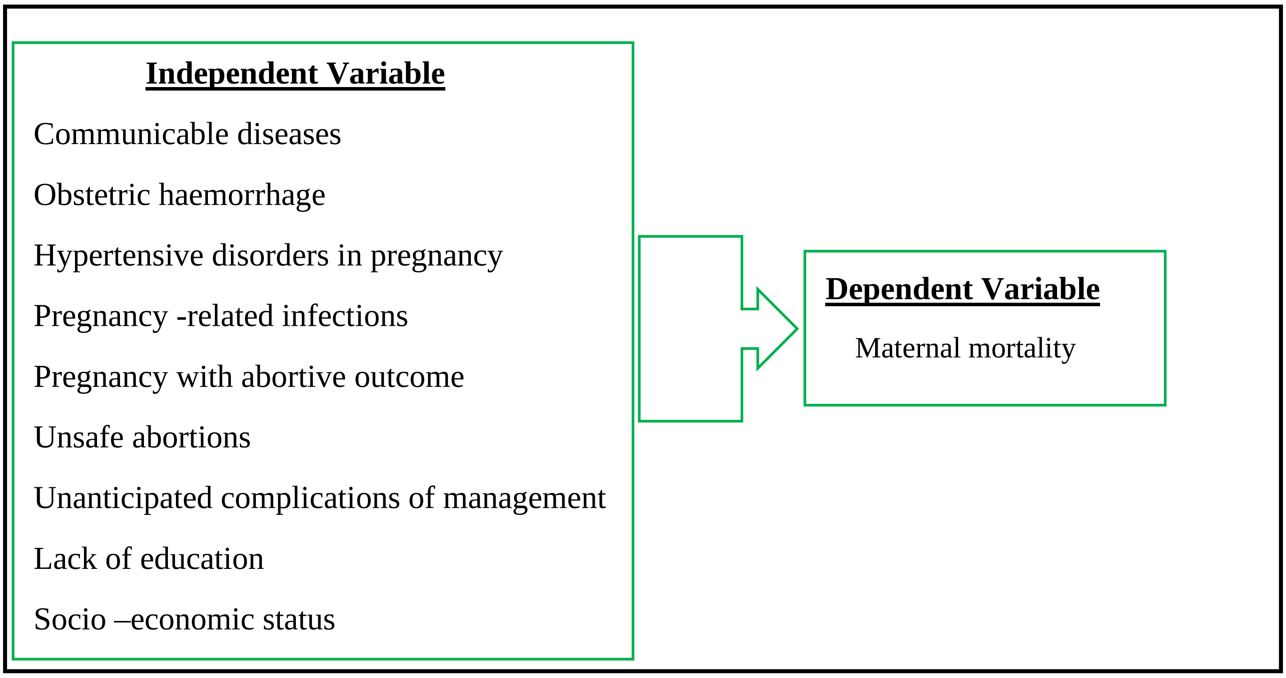
2.0 Introduction to the chapter

This chapter highlighted theoretical, conceptual framework and empirical review, concerning the subject at hand. The researcher gave summary of related literature.

2.1 Conceptual framework

According to Sahu (2016), conceptualization tries to show the relationship between variables focusing on the suspected effect one variable to the other. This framework is set before the research problem is explored so that the research is guided thus. In this research it is intended to explain the effects of independent variables on the subject matter. This relationship of the variable is shown in the diagram below (Figure 2.1):

Figure 2.1 Study Conceptual Framework



Source: Researcher own survey (2022)

The above variables were explained below (on section 2.4), including surveyed recent empirical literature.

2.2 Causes of maternal mortality

According to Amoo (2018), almost all situations that are associated with minimum or total lack of social support have an increased risk for maternal mortality. Someone who is single or divorced or widowed is part of the group that lacks support. Being one of several wives married to one man, cohabiting and self-supporting are also part of lack of social support. This is because there are too responsibilities facing one person and at the end many necessities will not be obtained hence this low socio-economic status may cause maternal mortality. As Amoo indicates theses unfortunate situations usually occur in rural areas.

World Bank (2015) report state that maternal mortality has reduced by 44% globally for about 532,000 in 1990 to an estimated 303,000 due to MDGs goal. The report highlighted that women die yearly due complications during pregnancy, childbirth, or perinatal period. The results of the report illustrated that mortality was high in developing countries. Fertility rates were high, and woman's maternal mortality risk was over 400 times higher than in developed nations. Further, there was an estimation of 20 million women enduring lifetime disabilities such as incontinence, anaemia, pelvic pain, and infertility which eventually may contribute to maternal deaths. According to WHO (2015) research, severe haemorrhages, unsafe abortions, illnesses connected to pregnancy, and obstructed labor are the primary causes of maternal death, while anemia, malaria, heart disease, and HIV are the indirect reasons.

UNICEF (2019) reports that for women between the ages of 15 and 19, issues are the main cause of death. High maternal mortality rates are a result of inadequate reproductive health care, including lack of access to professional care throughout pregnancy and delivery. Strengthening basic healthcare and healthcare systems is one of the most effective approaches to prevent maternal mortality. Family planning services have the potential to reduce maternal death and morbidity by 30%. Preventing unexpected pregnancies, having access to safe abortions as authorized by law, and obtaining post-abortion therapy should reduce maternal mortality and injury, as some 68,000 women die each year because of unsafe abortions. (Merchant and Boerma, 2020).

The Zimbabwe Maternal and Perinatal Death Study (ZMPMS) of 2017 found that postpartum haemorrhage, perinatal mortality hypertension, and eclampsia infections are the three main primary causes of maternal deaths in Zimbabwe. Indirect maternal fatalities caused by HIV, AIDS, and other conditions total around 36% of maternal deaths. The ZMPMS results are in line with regional research on maternal mortality, which place haemorrhage as the number one killer and hypertension as the second. In many developing countries, the problem of women's health and economic empowerment is rooted in gender inequality. Gender role models that prioritize male dominance and conventional patriarchal standards have a substantial impact. Many women do not have access to respectable employment that would allow them to overcome poverty or work in secure environments. Many people have yet to experience discrimination-free lives without the fear of being dismissed due to pregnancy or motherhood (Adedini, 2015).

2.3 Theoretical framework

2.3.1 Times series analysis

Peterson et al (2019) describes time series as a collection of ordered data. Although the ordering normally pertains to time, other orderings, such as over-space, could also be envisioned. If a time series' mean and variance remain constant, it is stationary. Both stationary and non-stationary time series are possible. All statistical prognostication techniques are extrapolatory in nature, which means they entail predicting future manifestations of historical patterns or relationships. Time series analysis is used to identify patterns of change in statistical data across predictable time intervals. (Henry, 2012). Understanding the formulas that divide a series into its component parts and atoms, enabling the detection of underlying trends, is the basis of time series analysis. It is primarily an attempt to understand the underlying context of the pertinent data points by the extrapolation of anticipated future values from observed past values. The SARIMA and ARIMA models are the focus of this study.

- Time series aspects

In time series analysis, random noise, also known as random error, which typically makes the pattern hard to find, and a systematic pattern, which is a set of distinguishable components, are thought to make up the data. The terms trend and seasonality refer to two different types of time series. A trend is an all-encompassing, systematic linear or (more commonly) nonlinear element that evolves over time and does not reoccur. Although the latter repeats itself over time at set intervals, it may have a formally similar structure (such as a plateau followed by an exponential growth stage).

- Trend analysis

The ability of "automated" systems to correctly recognize trend aspects in time series data has not been demonstrated. That portion of the study is often not too tough if the trend is monotonous. The initial step in the trend finding process is smoothing if the data are highly erroneous.

- Smoothing

To make the non-systematic components of individual observations cancel each other out, smoothing always entails local averaging of the data. The most popular method is moving average smoothing, which substitutes each element of the series with the weighted or simple average of adjacent items, where n is the size of the smoothing window. Instead of using means, you may utilize medians.

- Seasonal analysis

Another common element of the time series pattern is seasonal dependence (seasonality). A dependence of order k between each member of the series and the subsequent element is how it is technically defined. If the measurement error is not too great, seasonality can be seen graphically in the series as a repeating pattern.

- Autocorrelation

The correlogram (autocorrelogram) presents the autocorrelation function (and their standard errors) for successive lags within a predetermined range of lags graphically and numerically (e.g., 1 through 30). Because we often only care about extremely strong (and consequently highly significant) relationships, the magnitude of auto correlation is of greater relevance than its reliability. Through correlogram, seasonal trends in time series may be investigated.

- Lags

A period between two points or observations is defined as lag. This is a type of backward lagging, for instance, lag 1 is between Yt and Yt-1, lag 2 is between Yt and Yt-2, lag 3 is between í and í, and so on. The value of the observation at the current time, Yt, depends on the value from the previous time, Yt-0, with Yt being the difference between the two.

- Differencing

A formula for differencing involves deducting the value of an earlier observation from the value of a later observation. A dynamic mean's trend is eliminated by once or twice differencing, when the series is differenced, dC1 and linear trend are removed. This is the concept used to make the series stationary, to d-trend and control autocorrelations.

2.3.2 Arima model

To apply ARIMA, the data need differencing until stationarity is achieved. For this to take effect, the researcher used Augumented Dickey -Fuller test to achieve data stationarity. The appropriate ARIMA model was identified using ACF and PACF graphs. The researcher carried out diagnostic checking of AR and MA to conclude whether the model was adequate for data time series analysis. The appropriate ARIMA model was to be chosen using the Jenkins (1976) steps:

- **Model identification step** identifies the variables for analysing and confirming the stationarity of the time series, the best auto-regression and moving average combinations are chosen.
- The most effective model is chosen after a review of the ones found in the previous stage during the **model estimation phase**.
- **Model validation** phase evaluates the accuracy of the selected model and establishes any potential improvements.
- **Model forecasting stage** makes predictions about the series' upcoming data, which are provided with a confidence interval.

2.3.3 The box-jerkins Arima methodology

It refers to the set of procedures of identifying, checking, and fitting the ARIMA models with the time series data. After understanding this approach's forecasting potential, many scholars all around the world have started to apply the Box Jenkins technique to other fields, like weather forecasting. In this study, we will utilize it to predict maternal mortality and the maternal mortality ratio in BPH from 2010 to 2020. To choose a model, the researcher first differenced the series to attain stationarity, then looked at the correlogram to choose precise AR and MA components. This was followed by estimation of the tentative model and diagnostic testing. Thus, how the researcher applied ARIMA model as appropriate for series analysis.

2.4 Empirical review

Osoro (2014) employed descriptive retrospective study approach to analyse a two-year period on Kissi Hospital maternal mortality rate and the assumed causes of deaths. The research results highlighted that about 72, 40 and 33 maternal deaths were attributed to haemorrhage, pregnancy related infections and unsafe abortions respectively. The study results also indicated that financial instability led to challenges for consultation fees and check-ups. In addition, Savadogo (2014) study on maternal mortality causes indicated that Burkina Faso MMR increase was rural hospital distance in remote areas (more than 9km), few or no antenatal care visits), no emergency reference centres and age (women above 35 and young girls below 19).

Sarpong (2013) explored the MMR at the Okomfo Anokye Hospital (Ghana) using an ARIMA model and quarterly data for the years 2000 to 2010, and discovered that the ARIMA (1,0,2) model was the superlative for predicting as the MMR of 968 per 100,000 live births were found, relatively to government MMR statistics (980) in the region (Kumasi). Furthermore, Kitui (2013) employed multivariate analysis methods on his study of Kenya MMR and factors causing the increase of the ratio. The findings of the study had it that women death was high in remote areas where health facilities were distanced and had poor service delivery due to lack of exposure, education, and resources.

In Guinea-Bissau, a multicultural remote population, Rajia (2019) cites Haj (2013) study which evaluated demographic and perinatal risk factors for pregnancy-related mortality using a prospective survey. Their findings showed that repeated pregnancies, a woman's distance from the local hospital, and a prematurely born fetus all raised the maternal mortality ratio. Additionally, they discovered that women residing in the Gabu region died more frequently than those living in Biombo. They concluded that the screening strategy used in prenatal care has no effect in lowering maternal mortality. Cham (2013) examined the cultural, economic, and health service determinants influencing maternal fatalities in rural Gambia using a descriptive approach. According to the study, several significant factors, such as negative poor service delivery, delays in reaching a suitable medical facility, a lack of transport (ambulance) or time-consuming travel, seeking care at numerous healthcare centers, and delay in receiving response and proper care once at the hospital, all make a significant contribution to maternal deaths. Since factors related to health services were the most often identified causes of mother deaths, it was determined that increasing the caliber and accessibility of emergency obstetrical care services would considerably lower the MMR in the region.

Usman (2017) used simultaneous stepwise multiple regression to carry out a study on trends in Nigeria MMR. The study results illustrated that birth delivery by a skilled midwives and educational level of the women has great impact on MMR in Nigeria. A similar study based on stratified multi-stage cluster sampling previously done in the country by Fawole (2012) found that from the MMR of 927 per 100,000 live births, 80% of the women had done antenatal visit and 20% had not visited during pregnancy. Thus, there was a conclusion that low maternal education, lack of antenatal visits during pregnancy and mode of birth delivery (caesarean or normal) had impact in Nigeria MMR trends.

In addition, Lado (2015) assessment of the relationship between factors (causes of maternal mortality: independent variables) and maternal mortality (dependent variable) indicated that MMR was high in Chile due to abortions. The study results also indicated that women education level was a key factor and if enhanced MMR in the country would be reduced. Autoregressive models were used to assess the variables and 102 per 100,000 live births were estimated. Nyoni (2020) employed 'robust analytical methods' on MM for 180 countries and he found that since 1980 (526300) deaths to 342,000 deaths in 2008, the global MMR had diminished from 320 per 100,000 live births to 251 per 100,000 live births. The study results indicated that HIV had not been substantial catalyst to MMR increase in Africa.

2.5 Knowledge gap analysis

The discussed researchers above indicated the factors that led to increase of MMR in Africa using ratios and descriptive methods. As such to account for the discussed studies limitations, the researcher adopted ARIMA model to explain variables relationship in the past, present and predict the future values of the variables study. Moreso, despite vast existing research on the subject, maternal death rates remain high, and there is still no apparent answer to the issue. Most of the studies examined in the review were cross-sectional and conducted by affluent nations (developed) without the involvement of researchers from the developing nations. Without the participation of the developing countries, most studies in the body of literature were conducted by scholars from the developed world. Health research is underrepresented by work done by researchers from developing nations. Our analysis of the literature reveals that the impact of political and cultural factors on maternal deaths were disregarded. Socioeconomic aspects were the key macrostructural elements that were discussed by majority researchers. However, it has been demonstrated that political factors, such as democracy, have a significant impact on health indices, such as the MMR.

2.6 Summary of the chapter

In conclusion, the chapter was focused on review of existing literature on MM globally and how MM trend has been measured in other nations. For this study, the conceptual framework was acquired through expounding various data sources and meeting with midwives from a local clinic. Maternal mortality is attributed to the mode of delivery, age of the woman, distance to the facilities, educational level of the woman and poor service delivery due to poor socio-economic state etc. The relevant theoretical and empirical information were highlighted in this chapter. The methodology will be examined in the next chapter, which will also include the techniques and protocols used for data collection, analysis, and sampling. It will focus on the study sample selected, the tools utilized to gather the data, and the process followed for data analysis techniques.

CHAPTER 3

RESEARCH METHODOLOGY

3.0 Introduction to the chapter

The chapter provides a concise overview of the theoretical underpinnings of the models used in this study, the data collection process, formulae, and techniques of data analysis to achieve the study's goals, which are listed in Chapter 1. This chapter discussed the Box-Jenkins method for building an Autoregressive Integrated Moving Average (ARIMA) model that was used to anticipate time series patterns and the past, present, and projected future MMR for Bindura Provincial Hospital.

3.1 Research design

The researcher employed a quantitative analysis and descriptive statistics in the study on forecasting and trend analysis of BPH maternal mortality rate. An analysis of "large series of observations made on the same variable consecutively throughout time" was conducted as part of the study's longitudinal research approach. The study utilized time series analysis after commonly accessible data, such as those from the vital registration system, were analyzed to offer useful information at the local or national level. In such designs, a single subject or research unit is often monitored repeatedly at regular intervals over many observations. A longitudinal design may be compared to time series analysis as an example.

3.2 Research instrument

The time series data of maternal deaths encountered at BPH, analysed using e-views. The researcher also accessed secondary data using reports published on internet.

3.3 Target population and sample size

Active reproductive age group and women who have not reached menopause were the target population. The research sample consisted of all maternal (mortality) deaths and all pregnant women (15–49 years old) who were still alive throughout a 10-year period at Bindura Provincial Hospital (BPH).

3.4 Data source and collection procedure

The study focused on forecasting the patterns of Maternal Mortality at Bindura Provincial. The secondary data (maternal mortality: 2010-2020) employed was extracted from Bindura Provincial Hospital database. The researcher depended on various sources to confirm the accuracy of the hospital data. The data collected included yearly records of BPH maternal records. The data points of the study were 120 monthly observations under 10 years' duration.

Table 3.1: Study data sources

SOURCE	DESCRIPTION
Census	The researcher relied on 2021 census results on Bindura MMR
Household survey	The researcher relied on National Demographic Health Surveys as the surveys identify causes of death
Active age / Reproductive age death survey	The surveys investigate mortality of active age group and women who haven't reached menopause.
Zimbabwe Civil Registration System	The department register number of births and deaths

Source: Researcher own (2022)

The data had one dependent variable studied (maternal mortality) related to Bindura Provincial Hospital (BPH) MMR past ratios, current and estimated future values. The researcher presented maternal mortality as a ratio per year using the formula illustrated below.

$$MMR = \frac{\text{total maternal mortality}}{\text{total livebirths}} \times 100{,}000 \text{ livebirths}$$

3.5 Justification of the study

- **Hypothesis**

The researcher developed three hypotheses to test the relationship between variables:

- H1: There is a statistically positive significant relationship between maternal mortality and socioeconomic status, diseases, and education level. According to Scott (2019), MMR represents the risk associated with each pregnancy and factors affecting maternal mortality. In addition, maternal mortality variables study is essential for Millennium Development Goal Indicator for monitoring goal and improving maternal health.
- There is a statistically significant high maternal deaths at Bindura Hospital during the period 2010 and 2020. The forecasting of past trends allows the country health ministry to set reasonable and measurable goals based on current and historical data.
- There will be is a statistically significant high maternal deaths at Bindura Hospital between 2021 and 2025. The estimation of future trends gives the health ministry ability to make informed decisions and develop data-driven strategies.

3.6 Time series methodology

The primary goals of time-series analysis are control, forecasting, modeling, and description. The goal of time series analysis is to break down a time series' variance into its trend, periodic, and stochastic components (Sarpong, 2013). Box and Jenkins (1960) presented the ARIMA model, which is a forecasting extrapolation approach. Like all extrapolation methods, it just needs historical time series data for the variable being forecasted. The most significant methods for categorizing forecasting time series include the Box-Jenkins mode and Shrivastav and Ekata models. ARIMA is a forecasting extrapolation approach. Mishra (2012) stated that ARIMA is expressed as (p,d,q), in the prediction equation, p is the number of autoregressive elements, d is the non-seasonal changes, and q is the lags in the forecast errors. All that is needed are the historical time series data for the variable that is being forecasted. The most significant methods for categorizing predicting time series data are ARIMA models.

3.7 Data presentation and analysis

Trend analysis was performed by using Joint Point Regression and ARIMA technique to forecast the MMR for up to 2030. Joint point regression analysis was done using EViews 12 and ARIMA technique was performed through EViews 12. The MMR at Bindura Provincial

Hospital were distributed into a time series using ARIMA modelling for linear chats and autocorrelation charts. The time chart, or line chart, is essential to visualize the components and identify atypical values (outliers). ARIMA was used for forecasting as the technique used BPH past data to estimate future values. The study statistical analysis was done using SPSS. Trend analysis for maternal mortality and factors that influence it was conducted. The formula below was to examine the factors that affect MM.

Maternal mortality= *f (CD, OH, HDP, PRI, PAO, UA, UCM, LE, SES)* -------- *(i)*

Maternal mortality= $B_0 + B_1\,CD + B_2\,OH + B_3\,HDP + B_4\,PRI + B_5\,PAO + B_6\,UA + B_7\,UCM + B_8\,LE + B_9\,SES$

Where:

CD= Communicable diseases

OH= Obstetric haemorrhage

HDP= Hypertensive disorders in pregnancy

PRI= Pregnancy -related infections

PAO= Pregnancy with abortive outcome

UA= Unsafe abortions

UCM= Unanticipated complications of management

LE= Lack of education

SES= Socio –economic status

<u>Autoregressive Model- AR</u>

The model was based on M_t (maternal mortality at time *t*) was taken as an autoregressive process of order p that is AR (p) if weighted sum of the past p values plus random shock (Y_t)

- $M_t = {}_1 M_{t-1} + {}_2 M_{t-2} + {}_3 M_{t-3} + \ldots\ldots + Y_t$

  Employing the backward shift operator Y such that Y $M_t = M_{t-1}$ the AR (p) model was expressed as:

- $Y_t = (B)\, M_t$

  AR (p) process was expressed as

- $\mathbf{M_t = M_{t-1} + Y_t}$

When then the above equation becomes a random walk model; the series would be non-stationary (which is usual data for time series) and if the data would be stationery.

<u>M A Model (Moving Average Model)</u>

The moving average follows the order q, MA(q) if weighted the sum of last random shocks

- $M_t = Y_t + {}_{\mathbf{1}}Y_{t-1} + {}_{\mathbf{2}}Y_{t-2} + \ldots + {}_{\mathbf{q}}Y_{t-q}$

Employing the backward shift operator B equation was illustrated as

- $M_t = (B)\ Y_t \quad ((B) = 1 + {}_1B^1 + {}_2B^2 + \ldots + {}_qB^q$

Formula can be written as

- $\mathbf{M_t - {}_jM_{t-j} = Y_t}$

<u>ARIMA model</u>

AR and MA models are not usually employed by researchers because data is not stationary, hence with ARIMA combination of (pdq), the data needed differencing until stationarity is attained.

- 1st differencing: $M_t - M_{t-1} = M_t - B\,M_t$
- 2nd differencing: $M_t\,(1-B) - M_{t=1}\,(1-B) = M_t\,(1-B) - B\,M_t\,(1-B) = M_t\,(1-B)\,(1-B) = M_t\,(1-B)^2$
- 3rd differencing= $M_t\,(1-B)^2 - M_{t-1}(1-B)^2 = M_t\,(1-B)^2 - B\,M_t\,(1-B)^2 = M_t\,(1-B)^2\,(1-B) = M_t\,(1-B)^3$
- 4th differencing = $M_t\,(1-B)^d$

Therefore ARIMA (pdq) modelling MMR equation was

- $\mathbf{(B)\ (1-B)^d\,MMR_t = (B)\ Y_t}$

3.8 Summary of the chapter

The methodology chapter provided the data collection techniques, research design, research procedures and tools used in the study. The study employed secondary data that was gathered from the Bindura Provincial Hospital's records and database. The chapter further investigated the methodologies to be used in the research study. To generate inferential and descriptive statistics, models were highlighted that could help in the obtaining these results and outcomes. The measures of model accuracy and performance evaluation procedures were also discussed in this chapter.

CHAPTER 4

DATA PRESENTATION AND ANALYSIS

4.0 Introduction to the chapter

This chapter analyzes the study's findings considering the objectives of the study and provides a summary of the data presentation, discussions, and research interpretations. The presentation of descriptive data is based on the secondary data collected from Bindura Provincial Hospital databases. Stationarity has been tested before fitting the data into the model, the researcher used quantitative analysis on data analysis. Data comprising of yearly period maternal death and live births from 2010 to 2020 were obtained from Bindura Provincial Hospital and was used for analysis. Data was analyzed using SPSS and Eviews software.

4.1 Maternal mortality ratio for the study period

Table 4.1: Yearly maternal mortality ratios for Bindura Provincial Hospital

Table 4.1: Calculated Annual MMR

Year	Maternal deaths	Live births	MMR per 100,000 live births
2010	10	3089	324
2011	9	3160	285
2012	4	2196	182
2013	11	2586	425
2014	7	2884	243
2015	7	2716	258
2016	4	2722	147
2017	8	2679	299
2018	0	3152	0
2019	7	3387	207
2020	6	3360	179
TOTAL	**73**	**31931**	**2547**

Source: Researcher own survey (2022)

The table above shows the annual MMR per 100000 live births calculated by diving the total number of maternal deaths with the total live births for that year, multiplied by 100000, from the year 2010 to 2020.

4.2 Summary statistics

4.2.1 Descriptive statistics

Table 4.2: Descriptive statistics for yearly maternal deaths, live births and MMR per 100000 live births.

	Maternal Deaths	**Live births**	**MMR per 100000**
Mean	6.636364	2902.818	231.7273
Median	7.000000	2884.000	243.0000
Maximum	11.00000	3387.000	425.0000
Minimum	0.000000	2196.000	0.000000
Std. Dev.	3.107176	363.9170	109.9046
Skewness	-0.671794	-0.349424	-0.383618
Kurtosis	3.023157	2.336456	3.351994
Jarque-Bera	0.827643	0.425644	0.326585
Probability	0.661119	0.808300	0.849343
Sum	73.00000	31931.00	2549.000
Sum Sq. Dev.	96.54545	1324356.	120790.2
Observations	11	11	11

Source: Researcher own survey (2022)

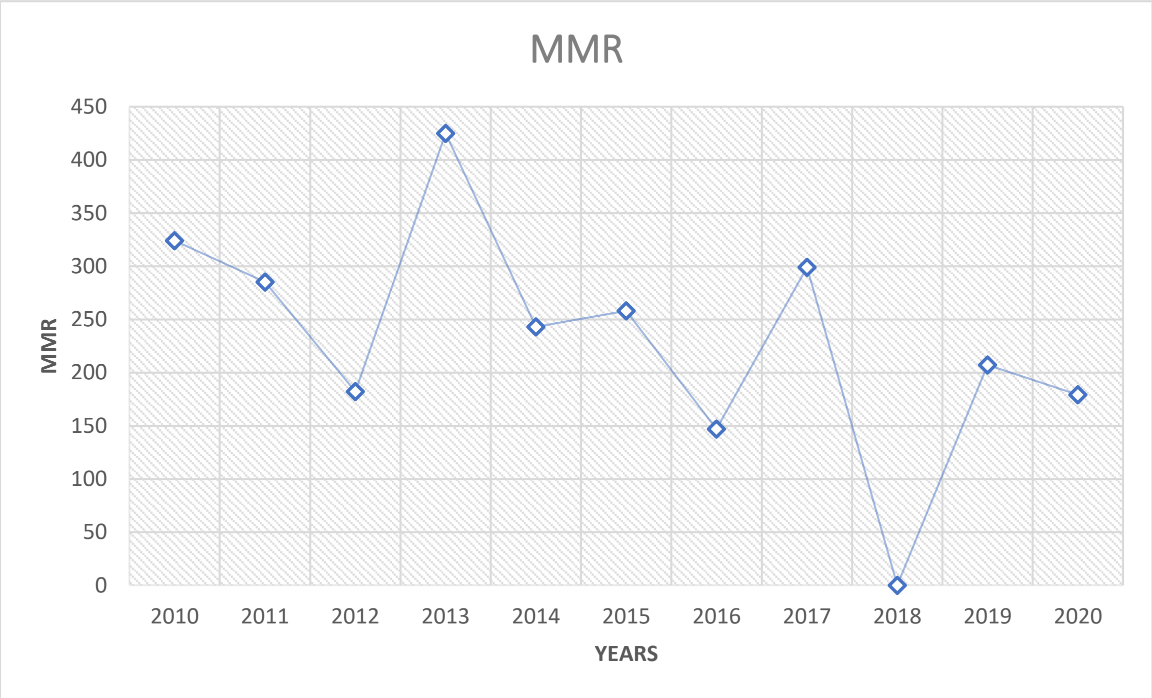
The above table shows the descriptive statistic for maternal deaths, live births and MMR per 100000 live births. The mean and skewness for MMR per 100000 live births indicates a negative relationship which implies that the MMR is decreasing. For dependent variables (maternal deaths and live births), also the mean is negatively associated with skewness, therefore showing that both variables are decreasing, which in the case of maternal death could be due to quality services provided by the health care facility, woman education on maternal mortality as well as the control of blood pressure. In the case of live birth there is a decrease which could be due to woman education and economic improvement with better living conditions.

4.2.2 Joint point regression analysis for MMR (Stationarity test)

Stationarity

Stationarity defines a time series whose statistical properties are constant over time. Stationarity is the main component in performing ARIMA. The researcher should ensure that the data is stationary before building the model. In this case, the researcher will use eViews Tests to test for trend stationarity and conduct an ADF for stationarity.

Figure 4.1: Graphical analysis for MMR trend



Source: Researchers own survey (2022)

The graph above shows that MMR is stationary.

Figure 4.2 Partial Autocorrelation function

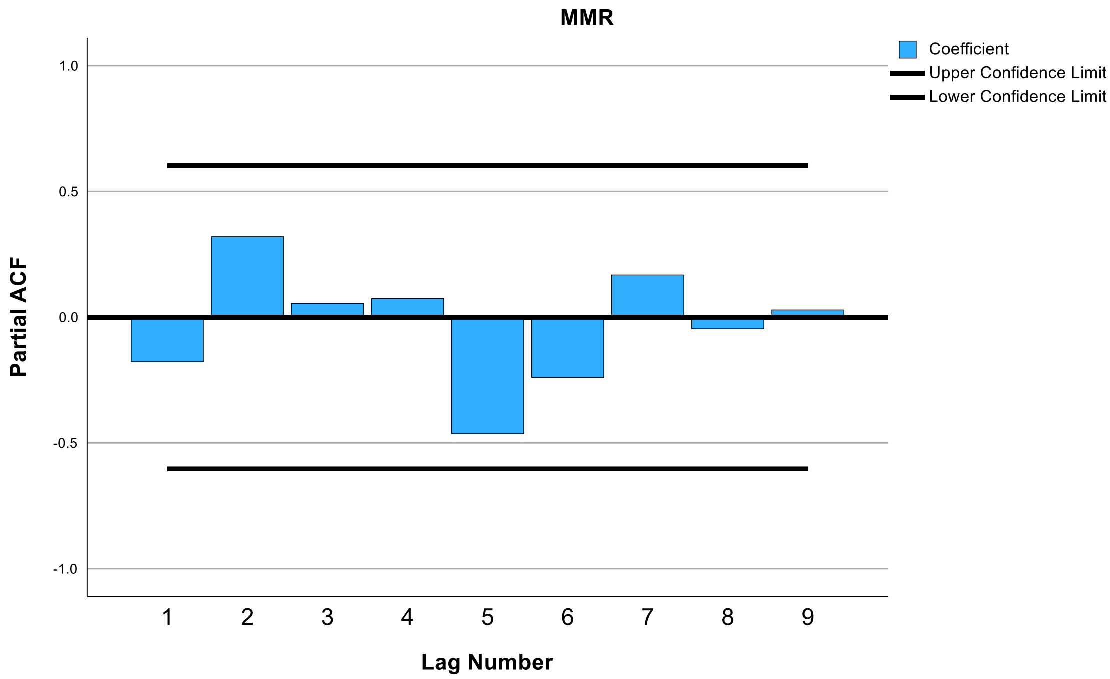


Figure 4.2 show autocorrelation function plot for MMR and the plot indicates that the data is stationary since all lags are within the confidence limit.

4.2.3 Unit Root Test Using ADF Test

Table 4.3 ADF Unit Root Test for MMR

	Intercept		**Trend and intercept**	
	Level	**1st difference**	**Level**	**1st difference**
MMR Per 100000	3.480856*	6.897906	5.037692	2.953854

*=1% significance level, **=5% significance level, ***=10% significance level

The table above shows the unit root test to check whether the MMR IS stationary at level or after a 1st differencing for both intercept and trend plus intercept. MMR is found to be stationary at level and intercept at 1% level of significance.

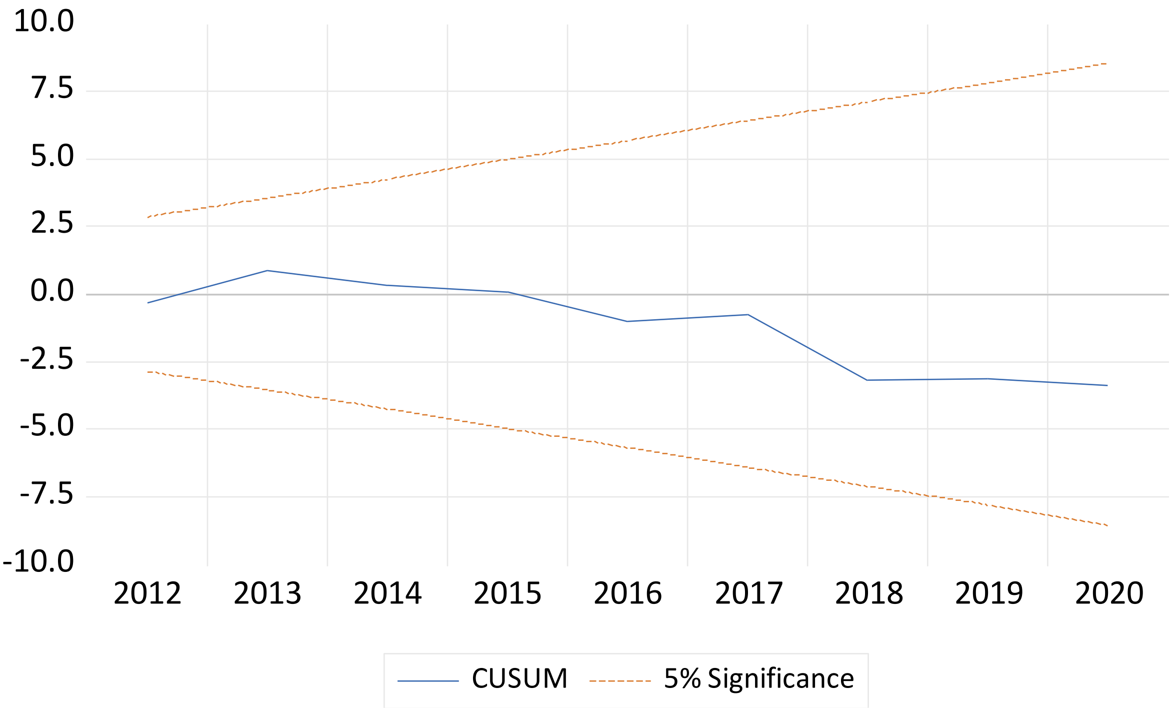
Table 4.3.1 ADF Unit Root Test Maternal Death and Live birth.

	Intercept		**Trend and Intercept**	
	Level	1st difference	Level	1st difference
Maternal death	3.925402*	3.349669	2.975811	2.993634
Live birth	1.657433	5.515843	4.886790*	4.886790*

Maternal death is stationary at level and intercept at 1% level of significance whereas live birth is found to be stationary at level and trend plus intercept.

4.3 Model Stability.

Figure 4.3: CUSUM test for stability.



CUSUM charts may recognize process alterations in the mean and variance as well as their change points (Wu, et al., 2007). The CUSUM tests graph above shows that our data for both maternal death and live births is stable since the blue line graph does not go beyond the red boundaries at 5% significance.

4.4 Model identification

The researcher will identify the time series model that's best fit for maternal mortality, the researcher will identify the Auto-Regressive and Moving Average terms that suit the model.

4.4.1 Parameter estimation

Table 4.4 AIC values of ARMA

ARIMA Model	AIC Value
(1,1,1)	12.66318
(1,1,0)	12.91206
(0,1,1)	12.74751

Source: Researchers own survey (2022)

According to the table the model with the minimum AIC value is ARIMA (1,1,1), with a value of 12.66318

Table 4.5: Box jerkins condition for the best model

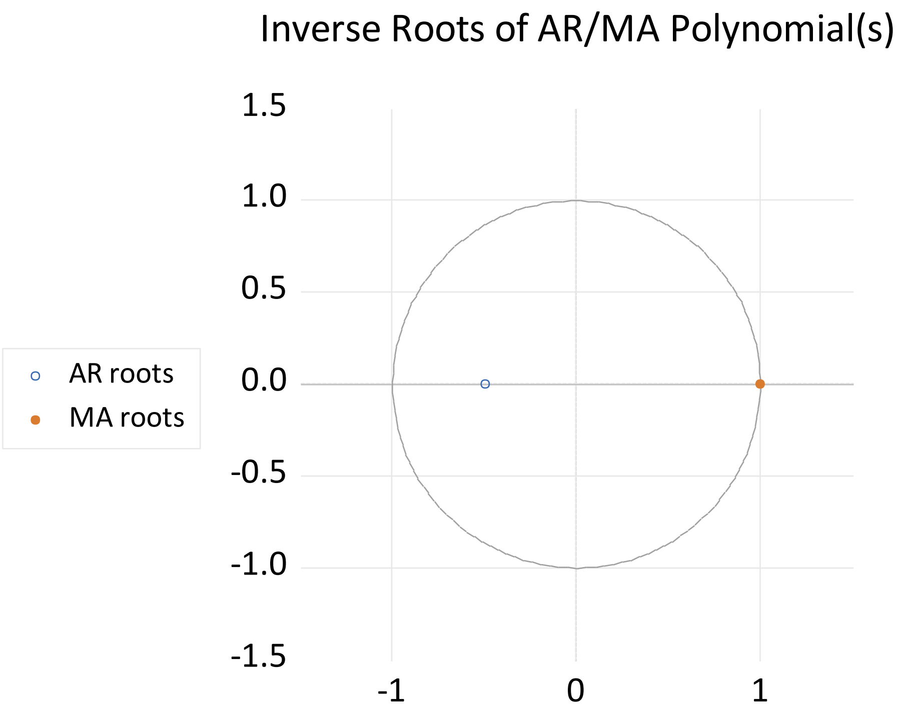
	ARIMA (1,1,0)	**ARIMA (0,1,1)**	**ARIMA (1,1,1)**
Sum Squared	108.1127	74.718118	**50.87387**
SIGMASQ	10.81127	7.471818	**5.087387**
Adj. R squared	0.391410	0.579395	**0.665890**
AIC	5.878380	5.688805	**5.607378**
SIC	5.969155	5.779580	**5.728412**

Source: Arima concepts (2020)

The table above shows the conditions for best model and ARIMA (1,1,1) has been found to be the best model since its sum squared, SIGMAQ, AIC and SIC values are minimum and its Adjusted R Squared value is the maximum value.

4.5 Model Fitting and Diagnostics.

Figure 4.4: Covariance stationarity



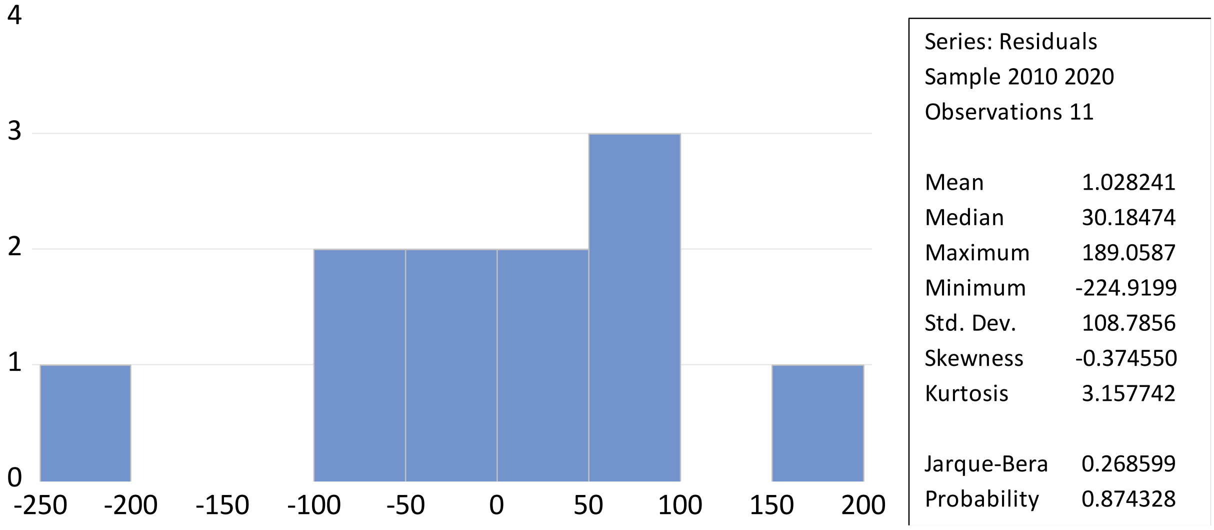
Source: Researchers own survey 92022)

AR roots lie inside the unit circle thereof this means our model is stationary.

4.6 Normality assumptions

- **Histogram of Residuals**

Figure 4.5 Jarque-Bera Test

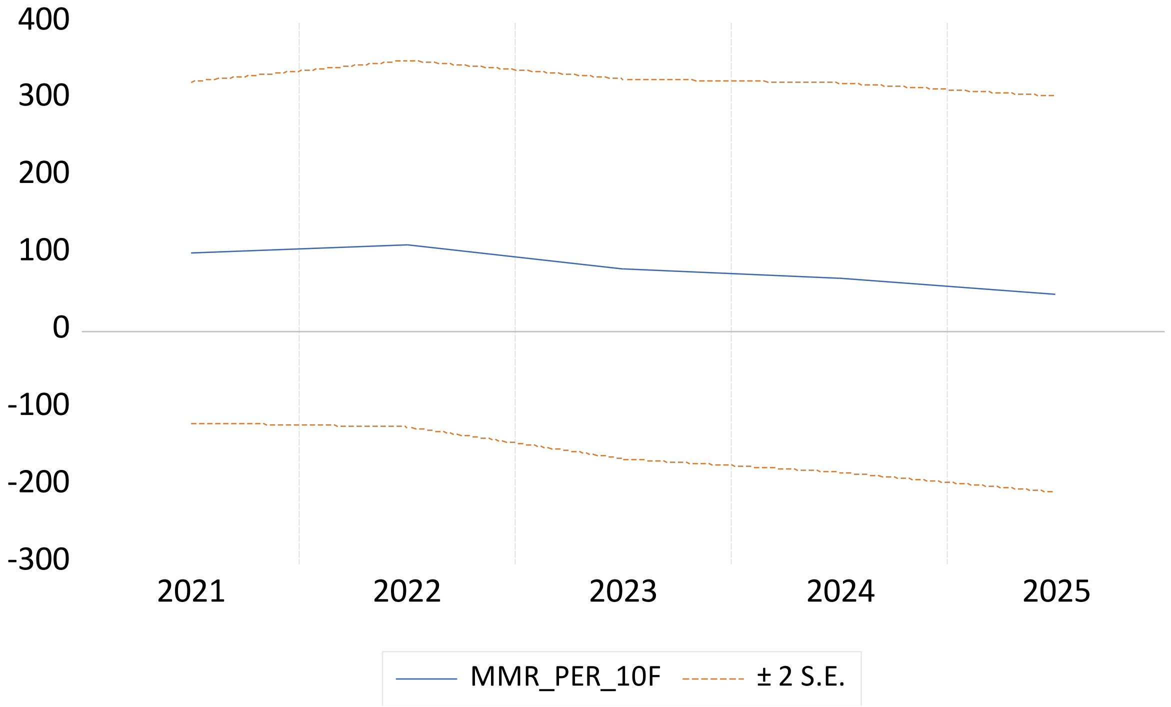


Source: Researchers own survey (2022)

The histogram above has a bell shape which shows normality of residuals; therefore the model meets assumptions of normality.

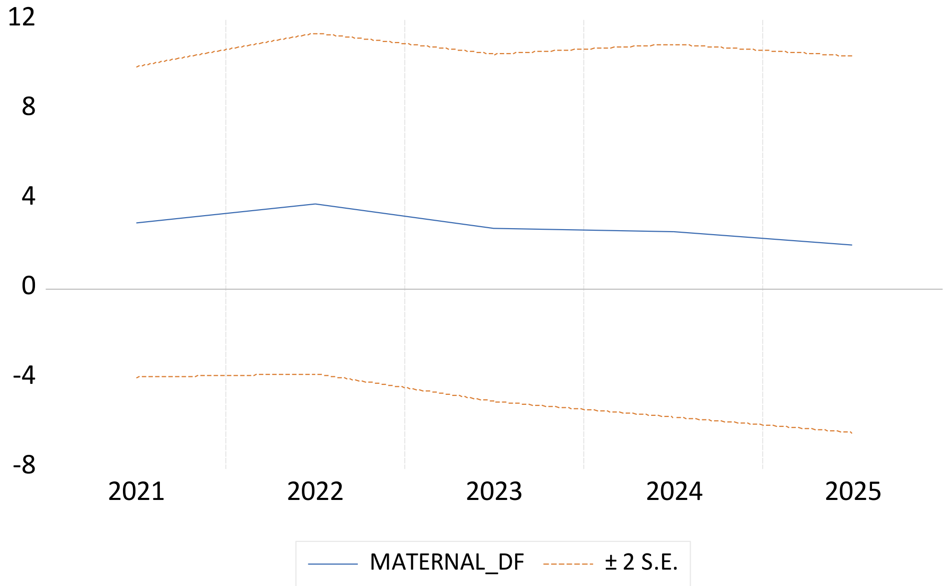
4.7 Forecasting results

Figure 4.6 MMR forecasted data



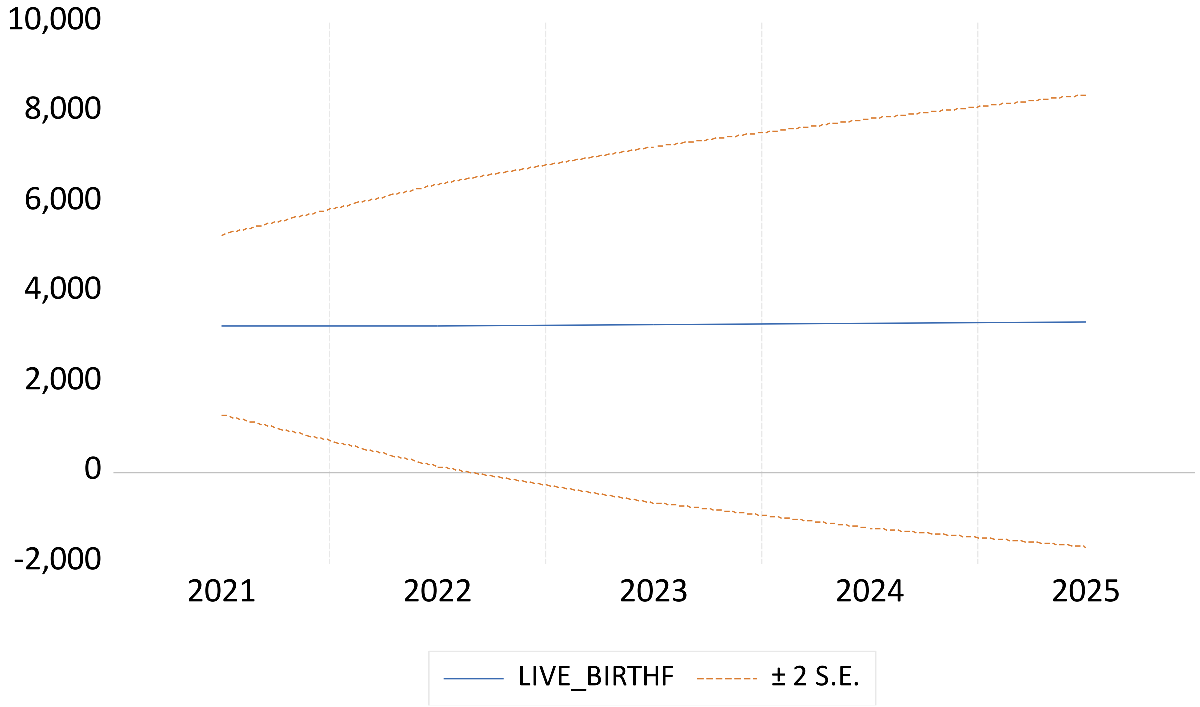
Source: Researchers own survey (2022)

Figure 4.7 Maternal death forecast.



Source: Researchers own survey (2022)

Figure 4.8 Live birth 5-year forecast



Source: Researchers own survey (2022)

The forecasted data graphs above show a constant change in all the three forecasts from 2021 to 2025.

Table 4.6 Forecast data

Year	Maternal Death	Live Births
2010	10.00000	3089.000
2011	9.000000	3160.000
2012	4.000000	2196.000
2013	11.00000	2586.000
2014	7.000000	2884.000
2015	7.000000	2716.000
2016	4.000000	2722.000
2017	8.000000	2679.000
2018	0.000000	3152.000
2019	7.000000	3387.000
2020	6.000000	3360.000
2021	2.961351	3271.810
2022	3.791767	3260.892
2023	2.697603	3281.075
2024	2.560779	3313.774
2025	1.947747	3351.511

Source: Researchers own survey

4.7. Summary of the chapter

This chapter looked at data analysis and data presentation which enabled the researcher to come up with the best time series model for the data through model diagnostic test. The ARIMA model that best fits the data was identified. Validity and stability of the model was detected using tests such as the CUSUM test for stability and ADF test for unit roots and non-unit roots.

CHAPTER 5

SUMMARY, RECOMMENDATIONS AND CONCLUSIONS

5.0: Introduction to the chapter

To allow for time series analysis of maternal mortality results, this chapter condenses the findings from the previous chapter. It also offers research results that are in line with the study's objectives. The researcher offers some recommendations at the end of the chapter, notably to the government, healthcare personnel, and the community that operates and lives in the same area where the study was performed, as well as the health care staff.

5.1 Summary of the study findings

The researcher studied on the time series of maternal mortality at Bindura Provincial Hospital from year 2010 to year 2020. Data was collected from Bindura Provincial Hospital, Health Information Department. The study's interests were on the trends of maternal mortality at Bindura Hospital. Related literature revealed the depth of concern maternal mortality has caused to the global world, Africa and most importantly Zimbabwe as a country. The researcher conducted research on the trends of maternal mortality at BPH. The researcher had to choose the most accurate time series model to anticipate maternal mortality over the following five years to get the best results. The researcher described the ARIMA and SARIMA models in the theoretical framework to forecast the trends in maternal mortality over the following five years. The research employed a descriptive research approach, and the data was processed using EViews software.

The first objective of identifying the best time series model for the data was explained in table 4.4, the researcher managed to come out with the best time series model to forecast maternal mortality at BPH. The best time series model was ARIMA (1, 1, 1). The model met all model diagnostic checks and selection criterions without violating time series assumptions. The researcher used several graphs to test for stationarity and also making the data stationary by differencing to obtain a suitable model for the data. The study was also aimed at achieving the objective of forecasting maternal mortality for the next five years which was done using eViews, the forecasted data was for the period from 2021 to 2025. The graph showed a constant trend on maternal mortality for the period from 2021 to 2025. The study focused only on maternal mortality ta BPH neglecting some health care organizations. This was because of unavailability of data to forecast future trends. Findings from the research showed that, the major challenge faced by Bindura Provincial Hospital was lack of sufficient information and poor technological skills to store and review their data, some of the data was stored as hard copies and were in poor state.

5.2 Conclusion

The research was effective because it was able to draw attention to the important concerns raised by the research topic and accomplish its goal. The research managed to analyse and model maternal mortality. From the findings of the research, we can conclude that the best fit time series model in forecasting maternal mortality at BPH was ARIMA (1, 1, 1). The research used annual maternal deaths the past 10 years for data analysis from the year 2010 to 2020. Review of literature on time series analysis was also conducted with useful empirical studies being considered. Forecasting was made using the Eviews 12 software package.

5.3 Recommendations

The recommendations led by the problem statement and summary findings of the study can be drawn

- The Health Information Department at BPH is therefore recommended to consider using the ARIMA model to analyse and forecast their data. The researcher has found that the ARIMA model is the most effective forecasting tool for the organisation. More so, they should store their data as soft copies and also revise the software they will be using to better and latest version.

- Based on the findings, the researcher recommends other scholars to conduct the forecasting process using different methods of forecasting to come up with the best fit time series model. Apart from that, other researchers can also further research on other health care organisations which were ignored by the researcher.

- The government should assist BPH with equipment and/devices for the storage of data, as well as create better systems or databases that accommodate most recent year capturing all the necessary information.

5.4 Suggested future work

Since data is varied, one data set's nature may differ from another's. A wider range of forecasting techniques may be compared as each has its own limits. The research may potentially use neural networks to handle non-linear data. The likelihood of getting a better forecasting model for the provided data will rise as a result.

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APPENDIX

Appendix A

Descriptive statistics

Date: 11/17/22 Time: 08:55
Sample: 2010 2020

	MMR_PER...
Mean	231.7273
Median	243.0000
Maximum	425.0000
Minimum	0.000000
Std. Dev.	109.9046
Skewness	-0.383618
Kurtosis	3.351994
Jarque-Bera	0.326585
Probability	0.849343
Sum	2549.000
Sum Sq. Dev.	120790.2

Date: 11/17/22 Time: 14:17
Sample: 2010 2020

	MATERNA...	LIVE_BIRTHS
Mean	6.636364	2902.818
Median	7.000000	2884.000
Maximum	11.00000	3387.000
Minimum	0.000000	2196.000
Std. Dev.	3.107176	363.9170
Skewness	-0.671794	-0.349424
Kurtosis	3.023157	2.336456
Jarque-Bera	0.827643	0.425644
Probability	0.661119	0.808300
Sum	73.00000	31931.00
Sum Sq. Dev.	96.54545	1324356.
Observations	11	11

Unit root test

Null Hypothesis: MMR_PER_100000_LIVE_BIRTHS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.480856	0.0335
Test critical values:	1% level	-4.297073	
	5% level	-3.212696	
	10% level	-2.747676	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations
and may not be accurate for a sample size of 10

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(MMR_PER_100000_LIVE_BIRTHS)
Method: Least Squares
Date: 11/17/22 Time: 09:05
Sample (adjusted): 2011 2020
Included observations: 10 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MMR_PER_100000_LIVE_BIRTHS(-1)	-1.177216	0.338197	-3.480856	0.0083
C	264.5002	88.15358	3.000448	0.0171

R-squared	0.602314	Mean dependent var	-14.50000
Adjusted R-squared	0.552603	S.D. dependent var	173.4886
S.E. of regression	116.0426	Akaike info criterion	12.52265
Sum squared resid	107727.1	Schwarz criterion	12.58317
Log likelihood	-60.61324	Hannan-Quinn criter.	12.45626
F-statistic	12.11636	Durbin-Watson stat	1.942457
Prob(F-statistic)	0.008309		

Null Hypothesis: MATERNAL_DEATHS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.925402	0.0173
Test critical values:	1% level	-4.297073	
	5% level	-3.212696	
	10% level	-2.747676	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations
and may not be accurate for a sample size of 10

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(MATERNAL_DEATHS)

Null Hypothesis: D(LIVE_BIRTHS) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.515843	0.0035
Test critical values:	1% level	-4.582648	
	5% level	-3.320969	
	10% level	-2.801384	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 8

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LIVE_BIRTHS,2)
Method: Least Squares
Date: 11/17/22 Time: 12:24
Sample (adjusted): 2013 2020

Model estimation and results.

Dependent Variable: D(MATERNAL_DEATHS)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/20/22 Time: 07:53
Sample: 2011 2020
Included observations: 10
Failure to improve objective (non-zero gradients) after 21 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.454841	0.264874	-1.717197	0.1368
AR(1)	-0.497428	0.434469	-1.144909	0.2959
MA(1)	-1.000000	43190.15	-2.32E-05	1.0000
SIGMASQ	5.087387	4863.304	0.001046	0.9992

R-squared	0.777260	Mean dependent var	-0.400000
Adjusted R-squared	0.665890	S.D. dependent var	5.037636
S.E. of regression	2.911869	Akaike info criterion	5.607378
Sum squared resid	50.87387	Schwarz criterion	5.728412
Log likelihood	-24.03689	Hannan-Quinn criter.	5.474603
F-statistic	6.979069	Durbin-Watson stat	2.234257
Prob(F-statistic)	0.022055		

Inverted AR Roots	-.50
Inverted MA Roots	1.00

Dependent Variable: D(MATERNAL_DEATHS)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/20/22 Time: 07:57
Sample: 2011 2020
Included observations: 10
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.347587	0.649638	-0.535047	0.6092
AR(1)	-0.671354	0.222264	-3.020521	0.0194
SIGMASQ	10.81127	8.752053	1.235283	0.2566

R-squared	0.526652	Mean dependent var	-0.400000
Adjusted R-squared	0.391410	S.D. dependent var	5.037636
S.E. of regression	3.929970	Akaike info criterion	5.878380
Sum squared resid	108.1127	Schwarz criterion	5.969155
Log likelihood	-26.39190	Hannan-Quinn criter.	5.778799
F-statistic	3.894138	Durbin-Watson stat	2.394410
Prob(F-statistic)	0.072968		

Inverted AR Roots	-.67

Dependent Variable: D(MATERNAL_DEATHS)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/20/22 Time: 07:55
Sample: 2011 2020
Included observations: 10
Failure to improve objective (non-zero gradients) after 1 iteration
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.445455	0.416513	-1.069485	0.3203
MA(1)	-1.000000	35686.67	-2.80E-05	1.0000
SIGMASQ	7.471818	5900.494	0.001266	0.9990

R-squared	0.672863	Mean dependent var	-0.400000
Adjusted R-squared	0.579395	S.D. dependent var	5.037636
S.E. of regression	3.267113	Akaike info criterion	5.688805
Sum squared resid	74.71818	Schwarz criterion	5.779580
Log likelihood	-25.44402	Hannan-Quinn criter.	5.589224
F-statistic	7.198868	Durbin-Watson stat	3.014951
Prob(F-statistic)	0.020024		

Inverted MA Roots	1.00

Forecast results

MMR Forecast

Last updated: 11/17/...
Modified: 2021 2025 =>
smpl 2021 2025for...

2010	324.0000
2011	285.0000
2012	182.0000
2013	425.0000
2014	243.0000
2015	258.0000
2016	147.0000
2017	299.0000
2018	0.000000
2019	207.0000
2020	179.0000
2021	237.6001
2022	231.3261
2023	231.3261
2024	231.3261
2025	231.3261

Live births forecast

2010	3089.000
2011	3160.000
2012	2196.000
2013	2586.000
2014	2884.000
2015	2716.000
2016	2722.000
2017	2679.000
2018	3152.000
2019	3387.000
2020	3360.000
2021	3271.810
2022	3260.892
2023	3281.075
2024	3313.774
2025	3351.511

Maternal death forecast

2010	10.00000
2011	9.000000
2012	4.000000
2013	11.00000
2014	7.000000
2015	7.000000
2016	4.000000
2017	8.000000
2018	0.000000
2019	7.000000
2020	6.000000
2021	2.961351
2022	3.791767
2023	2.697603
2024	2.560779
2025	1.947747

Appendix B

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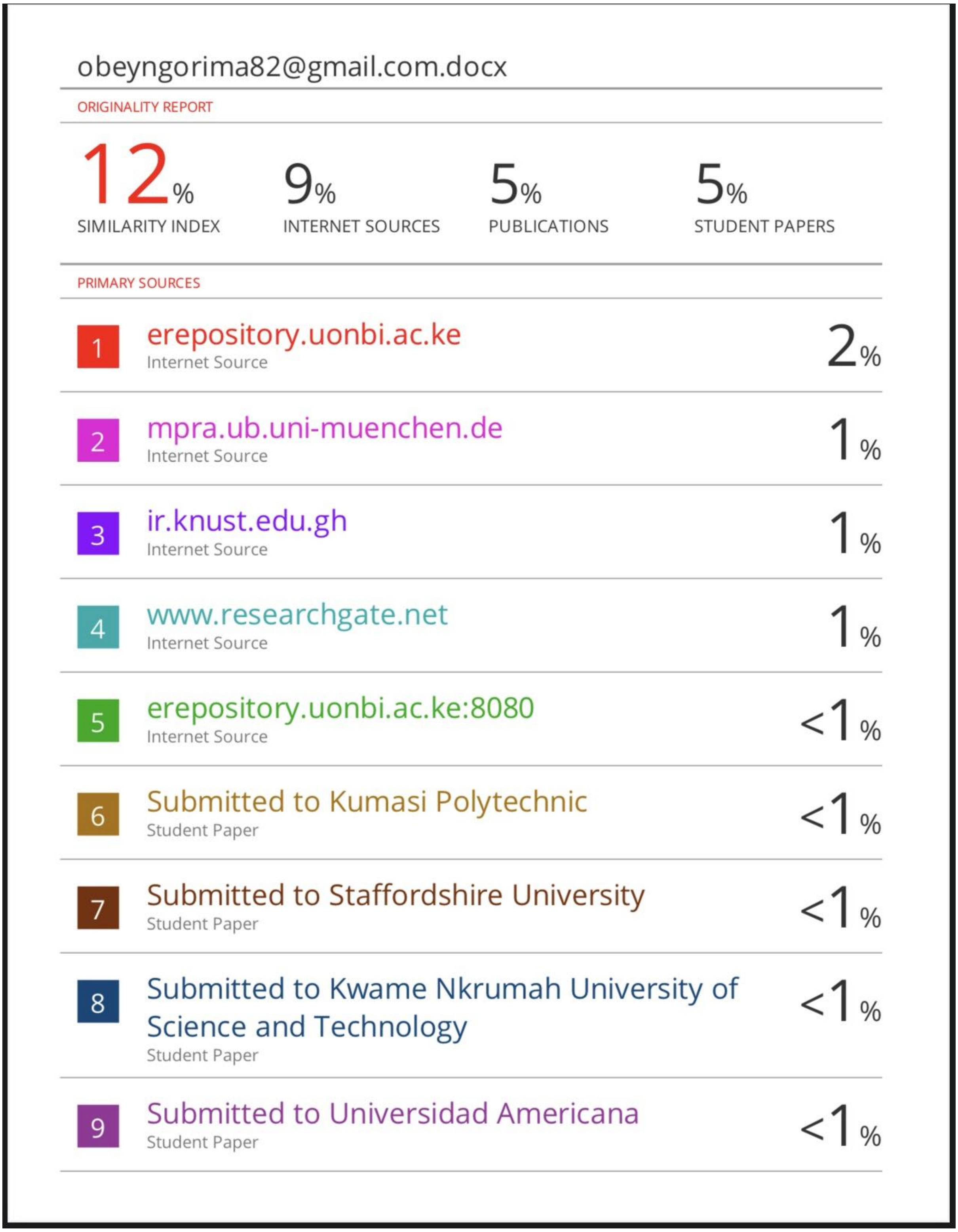

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