# TIME SERIES ANALYSIS AND SHORT TERM FORECASTING OF FEMALE CONTRACEPTIVES CONSUMPTION IN THE PUBLIC HEALTH SECTOR

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*A thesis in partial fulfillment of requirements for the award of the Degree of Masters of Pharmacy in Pharmacoepidemiology and Pharmacovigilance of the University of Nairobi.*

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## DEDICATION

*I dedicate this thesis to my parents for their immense support.*

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## LIST OF ABBREVIATIONS AND ACRONYMS

| | |
|---|---|
| ACF | Auto-Correlation Function |
| AIC | Akaike Information Criteria |
| ARIMA | Autoregressive Integrated Moving Average |
| ARMA | Autoregressive- Moving Average |
| BIC | Bayesian Information Criteria |
| CIP | Cost Implementation Plan |
| COC | Combined Oral Contraceptives |
| CPR | Contraceptive Prevalence Rate |
| DFID | Department of International Development (UK) |
| DHIS | District Health Information System |
| EACF | Extended Autocorrelation Function |
| ETS | Error, Trend and Seasonality |
| FBO | Faith-Based Organizations |
| FP | Family Planning |
| HIV | Human Immunodeficiency Virus |
| ICPP | International Conference On Population Development |
| IUCD | Intrauterine Contraceptive Device |
| KDHS | Kenya Demographic Health Survey |
| KEMSA | Kenya Medical Supplies Authority |
| KFW | Kreditanstalt für Wiederaufbau (German Funding Agency for International Development) |
| KHSSP | Kenya Health Sector Strategic and Investment Plan |

| | |
|---|---|
| LMU | Logistic Management Unit |
| MAE | Mean Absolute Error |
| MAPE | Mean Absolute Percentage Error |
| MASE | Mean Absolute Scale Error |
| ME | Mean Error |
| MoH | Ministry of Health |
| PACF | Partial Auto-Correlation Function |
| PMA | Performance, Monitoring, and Accountability |
| POP | Progestin-Only Pills |
| PPFP | Post-Partum Family Planning |
| PS Kenya | Population Services Kenya |
| RMHSU | Reproductive and Maternal Health Services Unit |
| RMNCAH | Reproductive, Maternal, Newborn, Child and Adolescent Health |
| RMSE | Root Mean Squared Error |
| SDG | Sustainable Development Goals |
| SDP | Service Delivery Points |
| UNFPA | United Nations Population Fund |
| USAID | United States Agency for International Development |
| WHO | World Health Organization |

## DEFINITION OF OPERATIONAL TERMS

**Commodity security:** When clients can access and use essential health commodities when and where they need them.

**Contraceptive Prevalence Rate:** Percentage number of women of reproductive age (15-49 years) currently using a contraceptive.

**Correlation:** A statistical method for determining the degree of relationship between continuous variables.

**Cross-validation:** A method of estimating the expected prediction error of forecasting models.

**Decomposition of time series data:** It is the separation of a time series data into its trend, seasonal, random and cyclical components.

**District Health Information System:** It is an online open source software platform developed by the Health Information System Programme for reporting, analysis, and dissemination of data for health programs.

**Mean absolute percentage error:** It takes the absolute value of forecast errors and averages them over the entirety of the forecast time periods. It is expressed as a percentage.

**Mean absolute scale error:** It a measure of forecasting accuracy.

**Method mix:** Percentage distribution of types of contraceptives used in a given country.

**Pull system:** A distribution system that is need-based. It is based on the customer's order.

| | |
|---|---|
| **Root mean squared error:** | It is a measure of the standard deviation of the prediction errors. It measures the amount of error between the predicted value and the observed value. |
| **Stationarity**: | A situation in a time series where the statistical properties such as mean and covariance are constant over time. |
| **Unmet needs**: | Fecund women who are not using contraception but who wish to postpone their next birth (spacing) or stop childbearing altogether. |
| **Theil's U**: | It is a measure of relative forecasting accuracy that compares forecasting results with the results of forecasting with minimal historical data. It helps to eliminate methods with large errors. |
| **Mean error**: | The average of the difference between the predicted and actual values. |
| **Mean percentage error:** | It is the mean error expressed as a percentage. |

## ABSTRACT

**Background:** Contraceptives security is crucial in ensuring access and delivery of family planning services and improving the contraceptive prevalence rate. Commodity security ensures that clients have access to commodities when and where they need them. It involves the integration of distribution systems, finances, health services, and policy guidelines. Proper forecasting, quantification, and procurement are critical in ensuring an adequate supply of contraceptives. It is important to study consumption patterns and apply forecasting techniques so as to adjust for any changes in the choice of contraceptives.

**Objective:** The overall objective was to evaluate trends in consumption and develop forecasting models for contraceptives consumption (injectables, pills, implants and intrauterine contraceptive devices) from 2014 to 2018 health facility reports.

**Methods:** The study was a time series analysis of family planning data. Data on consumption of implants, injectables, pills, and intrauterine contraceptive devices was extracted from the District Health Information System (DHIS2) which is an online platform for reporting health-related data in Kenya. Data cleaning and transformation was done to improve accuracy and data quality.

The first part of the analysis was exploratory where data for each contraceptive was evaluated for trend, seasonality, autocorrelation, and stationarity. This involved visual inspection of time series, correlogram and partial correlogram graphs and also carrying out statistical tests such as Ljung-Box test for autocorrelation and Augmented Dickey-Fuller test for stationarity. The data was also decomposed to evaluate the trends and seasonal components of the family planning commodity data. Comparison of consumption data on contraceptives and service point data was done using the time series correlation plots and correlation coefficients.

The second part of the analysis involved short-term forecasting (six months) using the Autoregressive Integrated Moving Average (ARIMA) models and the exponential smoothing with underlying state space models. Model diagnostics were done on the residuals of optimal models. Measures of the accuracy such as mean absolute percentage errors and root mean square errors were used to determine the optimal model. Validation of the models was done to estimate the prediction error of the models and this was done by comparing the forecasted consumption from January to June 2018 with the actual consumption.

**Results:** The consumption of pills, injectables and intrauterine contraceptive devices declined while that of implants increased from 2014 to 2017. There was seasonality in the consumption

patterns for each of the contraceptives. The lowest consumption was in December except for injectables and intrauterine contraceptive devices. There were differences in the data reported for consumption and service point data for injectables, implants and intrauterine contraceptive devices. The exponential smoothing models (ETS) were the best for forecasting consumption of all the contraceptives except for one-rod implants in which the Autoregressive Integrated Moving Average (ARIMA) model was more accurate. The ETS (M, N, N) was the best model for predicting consumption of progestin-only pills and intrauterine contraceptive devices. It tended to give underestimates with a mean error of -0.109 and -0.054 respectively. The ETS (A, N, N) was optimal for predicting consumption of combined oral contraceptives and injectables. For combined oral contraceptives the forecasts tended to overestimate with a mean error of 0.136 while for injectables it underestimated with a mean error -0.117. The ETS (A, A, N) was the optimal model for two-rod implants and it gave overestimates with a mean error of 0.052. The only contraceptive for which the ARIMA model was superior to the ETS models was for the one-rod implant. For this model, ARIMA (1, 1, 3) gave the lowest mean error for all methods considered with a mean error of 0.048.

**Conclusion:** There was a general shift towards the use of long term reversible methods especially implants in Kenya. The difference in the reporting of consumption and service point data for injectables, implants and intrauterine contraceptive devices showed that there was a gap in the documentation and the reporting of the consumption and service point data. The ETS models were generally superior to the ARIMA models for predicting consumption of contraceptives.

# CHAPTER ONE: INTRODUCTION

## 1.1 Background

Family planning (FP) is the regulation of the number of children born and the spacing interval between them by use of traditional or modern contraceptive methods. Promotion of family planning practices and the supply of preferred contraceptives and services for women and couples is essential in improving the wellbeing and freedom of women. These practices reduce the risk of unwanted pregnancies and the need for abortions which may contribute to maternal morbidity and mortality. It also reduces infant mortality by preventing closely timed pregnancies. Some family methods like condoms lower the chances of contracting sexually transmitted infections as well as HIV. Family planning has a long-term advantage of empowering women by enhancing education, increasing productivity and controlling population growth (1).

The 2010 Constitution of Kenya, Article 43, protects every individual's right to access the highest level of health in addition to reproductive health services (2). The Reproductive Bill, 2014, Part Two requires the National and County governments to provide reproductive health services and commodities to its citizens (3). It is therefore paramount for the Government to ensure access to preferred FP services and commodities as described in various laws and assist in the attainment of the Sustainable Development Goals (SDG's) by 2030. The Reproductive and Maternal Health Services Unit (RMHSU) in the Ministry of Health is mandated to implement and monitor programmes geared towards the promotion of reproductive health (4).

Modern family planning methods include intrauterine contraceptive devices, injectables, progestin-only pills, combined oral contraceptive pills, sterilization, and basal temperature methods. The traditional methods of family planning are the calendar or rhythm method and withdrawal. In Kenya, the most regularly used modern contraceptives among women are injectables, pills, implants and intrauterine contraceptive devices (5).

The contraceptive prevalence rate is the number of women of reproductive age currently using a contraceptive. According to the World Health Organization (WHO), the world's Contraceptive Prevalence Rate (CPR) for modern contraceptives was 57.4% in 2015. This was a slight increase from 54% in 1990. The unmet need for contraceptives is estimated to be about 225 million women. In Africa, the CPR is 28.5% (2015) which is a slight increase from 23.6% in 2009. The unmet need for contraception in Africa was 24.2% among women of reproductive age and this was attributed

to insufficient family planning services and growth of populations (1). In Eastern Africa, contraceptive use in 2015 was at 40% while the unmet needs for contraceptives were 24.2% (6).

In 2014, the CPR among married women in Kenya was 58% with 53% being on modern methods and 5% on traditional methods (5). The CPR for modern methods among sexually active unmarried women between 15-49 years was 65% with 61% using modern methods. The use of modern methods in Kenya has been on the rise for the last decade. This was evidenced by an increase from 32% in 2003 to 53% in 2014. Despite the increase, there is still an unmet need of 18% among married women (5). The unmet need is 13% in urban areas and 20% in rural areas. The North Eastern region has the highest unmet need at 30% and the Central region has the lowest at 9% (5). In 2015, Kenya had a CPR of 57.4% and an unmet need of 18.5% (6).

Family planning commodity security ensures access and provision of FP services and increasing the CPR. Commodity security ensures that clients have access to commodities when and where they need them. The family planning program in collaboration with various partners is charged with the responsibility of ensuring contraceptive commodity security. It involves the integration of distribution systems, finances, health services, and policy guidelines. Proper forecasting and quantification and procurement is critical in ensuring an adequate supply of FP commodities.

There are various challenges that hinder proper quantification and procurement m of FP commodities. This includes inadequate financing, lack of technical know-how, inaccurate data on consumption, overdependence on donor funding and improper method mix. Some of the consequences of improper quantification are stock-outs, expiries, unsatisfied clients, reduced CPR and increased unmet needs. Shortages of contraceptives are one of the leading causes of discontinuation of contraceptives and a reason for turning away clients by health care providers. Stock-outs of other accessory items such as syringes for injectables also affect family planning services utilization (7).

Lack of family commodities in health facilities can result from expiries of commodities or stock outs. Stock-outs are experienced commonly in health facilities providing family planning services from time to time and at varying levels (8). Lack of these commodities limits accessibility to the desired choice of contraceptives by women and contributes to the unmet need for contraception (9).

## 1.2 Research problem

There has been no study done utilizing actual data collected from Kenyan health facilities to analyze trends and changes in method mix. Using the District Health Information System (DHIS2) data is likely to reflect a more accurate trend of the consumption data as it represents actual use of contraceptives as recorded by health care workers as opposed to the KDHS which depends on the recall of respondents during surveys (5). There have been a few studies utilizing data collected during the Health Demographic Surveys to analyze trends in changes in method mix and the CPR among in union and married women aged 15 to 49 years (6,10,11)

Failure to study trends in consumption of contraceptives leads to the procurement of inappropriate quantities which result in waste due to expiries and stocks outs hence drops in consumption. It is, therefore, useful to study the consumption trends of these commodities so as to adjust for any changes in demand and preferences. Changes in preferences influence the method mix and prioritization of various contraceptives.

Time trend analysis of consumption of contraceptives and comparison of reported service statistics consumption levels has also not been done before. This study aimed at carrying out a time trend analysis of consumption levels from 2014 to 2017 and compare data collected at the service point and consumption levels of contraceptives to inform procurement activities of the same and 2018 as the forecasting period.

## 1.3 Research questions

1. What are the consumption trends for injectables, implants, pills and intrauterine contraceptive devices?
2. Does consumption of these commodities show a seasonal or cyclic pattern?
3. How does service statistics correlate with reported consumption levels of FP commodities?
4. What is the likely consumption of FP methods in the next 6 months?
5. Which is the optimal time series model for predicting consumption?

## 1.4 Study objectives

The overall objective of the study was to analyze the consumption of contraceptives (Pills, injectables, IUCDs, and implants) in the public sector between the year 2014 to 2017 so as to identify consumption trends and forecast consumption for January to June 2018.

### Specific objectives

The specific objectives were to:

1. Analyze the consumption trends for pills, injectables, IUCDs, and implants.
2. Identify any seasonal or cyclic patterns in the consumption of the contraceptives.
3. Compare consumption data and service delivery point data for contraceptives for implants, IUCDs, and injectables.
4. Forecast consumption patterns of the contraceptives for the next 6 months.
5. Determine the optimal time series model for predicting consumption.

## 1.5 Study justification

The study will inform the procurement of contraceptives in Kenya by evaluating trends in their consumption. This will improve quantification and therefore reduce shortages and expiries associated with under and oversupply respectively. This will lead to cost savings and improved service delivery.

There have been a few studies utilizing data collected during the health demographic surveys to analyze trends in changes in method mix and the CPR among in union and married women of ages between 15 and 49 years (6,10,11). However, there has been no study on contraceptives consumption using facility data in Kenya.

Correlation between service delivery point data and consumption data will help identify areas of under and/or over-reporting, wastages of commodities and shortcomings in the documentation. This will inform targeted capacity building for health workers and eventually improve service delivery. The forecasts will improve quantification process of contraceptives.

## CHAPTER TWO: LITERATURE REVIEW

### 2.1 Contraceptive methods in Kenya

There are two main family planning methods, traditional and modern. The modern contraceptive methods consist of injectables, pills, implants, male & female condoms, sterilization, lactation amenorrhea, standard days, basal body temperature, two days and the symptom-thermal method. The traditional methods are the rhythm or calendar and withdrawal method (1).

This time series analysis study focused on the most commonly used modern contraceptives in Kenya according to KDHS 2014. These were injectables, pills, implants and intrauterine contraceptive devices of which public sector supplies 60 % of all contraceptives in Kenya (5).

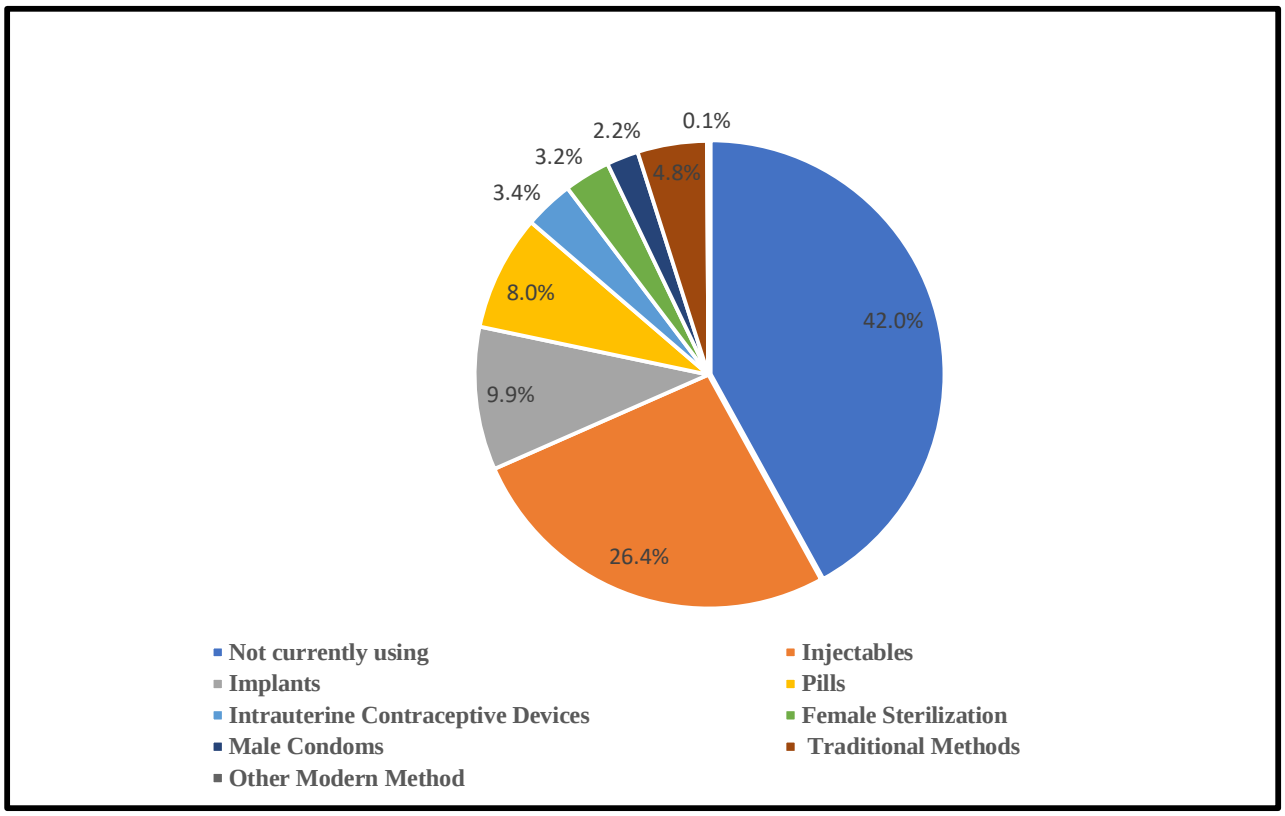


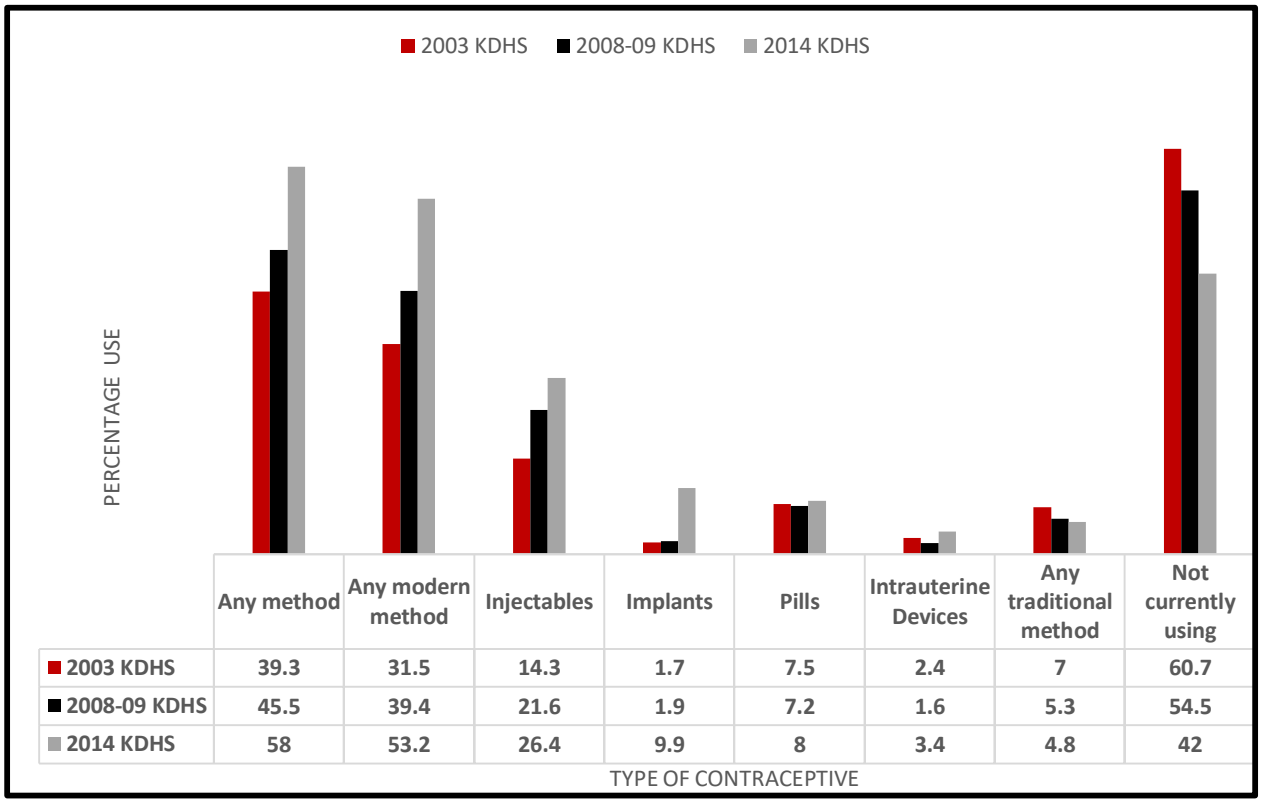

Figure 2-1: Percentage commodity mix for various contraceptives - KDHS 2014

Forty-two percent of the population was not using any form of contraceptive in 2014. The most prevalent contraceptive was injectables followed by implants. Male condoms were the least popular with a prevalence of use of 2.2% (5).

## 2.2 Method mix of contraceptive methods

The percentage of women using different modern contraceptive methods is referred to as method mix. It is a proxy measure for the obtainability of different kinds of contraceptive methods in a country during surveys (11). This ensures the different needs and preferences of different women are met.

Method mix measurement done during forecasting and procurement in Kenya is guided by service point data, health surveys, and consumption data. (12). There has been a shift towards the use of injectables in sub-Saharan African including Kenya as opposed to other methods (5,6,13). Based on the 2008-2009 KDHS Kenya was classified to have a borderline skewed method mix due to high use of injectables, where 45 to 49.9% of the users relied on one form of contraceptive (11).




| | Any method | Any modern method | Injectables | Implants | Pills | Intrauterine Devices | Any traditional method | Not currently using |
|---|---|---|---|---|---|---|---|---|
| 2003 KDHS | 39.3 | 31.5 | 14.3 | 1.7 | 7.5 | 2.4 | 7 | 60.7 |
| 2008-09 KDHS | 45.5 | 39.4 | 21.6 | 1.9 | 7.2 | 1.6 | 5.3 | 54.5 |
| 2014 KDHS | 58 | 53.2 | 26.4 | 9.9 | 8 | 3.4 | 4.8 | 42 |

Figure 2-2 Trends in percentage use of various contraceptives from the 2003, 2008-09 and 2014 KDHS

### 2.2.1 Patterns of use of injectable contraceptives

In 2015, only 5% of in-union or married women were using injectables worldwide. Nevertheless, they are commonly used in Eastern and Southern Africa(6). Injectables are the most popular choice

of contraception in Kenya accounting for 26% use among married women. Injectables are popular because of ease of use, availability in both public and private facilities and immediate return to fertility (14). The use of injectables among married women has been gradually rising over the years; 14% in 2003 to 26% in 2014 (5) as presented in Figure 2-2. In 2009, injectables use among married women in Sub-Saharan Africa (6.8%) was double the world's average rate of 3.5% (10). Only 28.1% of women between the age of 15 to 49 years used injectables in 2015 (6).

In Kenya, Depot Medroxyprogesterone Acetate (DMPA) is the only injectable supplied to government health facilities (12). It is also marketed as Femiplan™ in the private sector. Depot medroxyprogesterone acetate, commonly referred to as Depo Provera™, is a progestin-only injectable which is injected intramuscularly in the gluteal or deltoid muscle (150 mg every three months) (15). It is associated with a 1% failure rate when used consistently and correctly. It acts by stopping ovulation and also thickens the cervical mucus thereby inhibiting the sperm from reaching the egg but is generally associated with irregular vaginal bleeding and amenorrhea (1,15).

### 2.2.2 Patterns of use of pills

The percentage of women in the world using pills in 2015 stood at 9%; Africa's use was at 9.8%. Pills were the most common method in use in over 70% of the countries in the world. This because they were easily available and cheaper compared to other methods (6). According to KDHS 2014, 8% of married women were on pills. The proportion of married women in Kenya on pills has been stable over the years; 8% in 2013, 7% in 2008-09 and 8% in 2014 as presented in Figure 2-2 (5). The United Nation reported that 8.6% of in union or married women between 15 to 49 years in Kenya used pills in 2015 (6). These pills are the progestin-only pills and combined oral contraceptives.

Combined oral contraceptives contain two synthetic hormones; progestin and an estrogen. They are taken on a daily basis to ensure effectiveness. They act by thickening cervical mucus and suppressing ovulation. The combined oral contraceptives used in the public sector are monophasic as they contain equal amounts of estrogens and progestins. The pills are only effective when used consistently and correctly (16,17).

Progestin-only Pills (PoPs) are similarly known as the minipills. They contain progestins and are the pills of choice for breastfeeding women as they do not suppress milk production, unlike the

combined oral contraceptives. They act by thickening of the cervical mucus thus stopping the sperm from reaching the ova (16).

### 2.2.3 Patterns of use of implants

In 2015, only 0.7% of in union and married women from ages 15 to 49 years in the world were using implants. In Africa, implants use was at 2.3 and 10.8% in Kenya (6). According to KDHS 2014, the percentage of married women of ages 15 to 49 years using implants was 9.9. The use of implants has increased since 2008/2009 KDHS from 1.9 to 9.9 % as presented in Figure 2-2 (5).

There are two brands of implants in the Kenyan public sector, Jadelle® and Implanon®. Jadelle® is a two-rod implant containing 75mg levonorgestrel each and is active for five years. Implanon® is a one-rod implant containing 68mg of etonogestrel and is active for 3 years. They are inserted under the skin in the arm and release the hormone slowly. They act by thickening cervical mucus (16,17).

### 2.2.4 Patterns of use of intrauterine contraceptive devices

Intra-uterine contraceptive devices were the most commonly used method of contraception after female sterilization in the world. In 2015, it accounted for 14% of contraceptives used among women aged 15 to 49 years worldwide. Only 3.8 and 3.5% of the in-union or married women were using intrauterine contraceptive devices in Africa and Kenya respectively (6). In the KDHS 2014 survey, 3.4% of married women were using intrauterine contraceptive devices. There was a decline in their use from 2.4% in 2003 to 1.6% in 2008/2009 followed by an increase to 3.4% in 2014 as presented in Figure 2 -2 (5).

Intrauterine contraceptive devices are flexible devices which are inserted into the uterine cavity. They are of two types; hormonal based and copper-based devices. Copper-based intrauterine contraceptive devices are the most commonly used in Kenya. Copper-based devices act by releasing copper thereby preventing fertilization. They prevent sperms from reaching the fallopian tube (16,17).

### 2.2.5 Factors influencing the use of contraceptives

The level of education affects the knowledge about contraceptives and their use. In 2014, about 98% of women of reproductive age were cognizant of the modern contraceptive methods compared to 99% of men in the same age category (2014, KDHS). Men and women without formal education

had less knowledge about any contraceptive (87.8 and 94.7% respectively)in comparison with those who had secondary education and above (100%) (5).

Contraceptive use was greater among educated women than those who were not. Only 65.3% of married women with secondary education and beyond used modern contraceptives compared to 17.7 % who had no education. The wish to limit the number of children sired rose with the level of education. However, for women living in Bangladesh and Bhutan Philippines, uneducated women were more receptive to contraceptive methods in comparison to the educated ones. This was attributed to knowledge of side effects among the educated women (18). The level of education is, therefore, a double-edged sword when determining the choice of contraceptives. Educated women have a higher propensity of using modern methods compared to uneducated ones but this may also limit the use of contraceptives owing to the knowledge of side effects and thus avoid them.

Use of contraceptives varies depending on whether one is living in urban or rural areas. In 2014, 61.8% of women between the age of 15 to 49 years in urban areas were using contraceptives compared to 55.5 % of women resident in rural areas (5). Women resident in urban areas have access to an extensive assortment of contraceptive methods which suits their needs compared to those that reside in rural areas (19). Use of pills, intrauterine contraceptive devices and implants were highest among women living in urban areas at 10.7, 4.7 and 12% respectively in comparison to women in the countryside at 6.2, 2.6 and 8.6% respectively. However, the use of injectables is higher in the countryside at 27.5% compared to urban areas at 24.7% (5).

Religion is a strong factor in the consumption of contraceptives. Acceptability of contraceptives differs across religious beliefs; Protestants are inclined to use contraceptives more than Muslims, making religion one of the main factors influencing the use of contraceptives amongst women in North Eastern Kenya where there is a large population of Muslims (20). This is reflected by a low contraceptive prevalence rate of 3.4% in North Eastern province compared to the national value of 58% (5). A local study was done at Kisii level five hospital to evaluate the factors affecting contraceptive use among breastfeeding women, showed that 90% of Protestants accepted contraceptives compared to 40% of the Muslims (18). Non-Catholics were likely to use contraceptives compared to Catholics. (21) A study in Ghana on unmet needs of contraception

showed that women without any religious backgrounds had the least unmet needs compared to those with religious backgrounds. (22)

Mass media campaigns also play a role in imparting knowledge and increasing awareness of contraceptives. Most men and women had access to mass media campaigns according to the 2014 KDHS with men having more exposure than women. Messages on family planning got through radio were more common compared to other modes of mass media campaigns such as television newspapers, and magazines (5). About 20% of women and 10% of men had not heard any family planning messages through any form of media (5). Women who had access to family planning messages were predisposed to use contraceptives in comparison to women who did not (5,20).

Women with one or more children used contraceptives more compared to women without living children. In the 2014 KDHS, only 15 % of women without living children were using contraceptives compared to 61% of women with one or two children. This number increased among women with three or four children at 66% (5). A study done at Kenyatta National Hospital showed an important relationship between the number of children a woman had and contraceptive use (14).

### 2.3 Policies on family planning and commodity supply in Kenya

Policies have a great effect on the provision of family planning services in Kenya. Kenya has adopted various international declarations and partnerships with regard to family planning services. In 2015, Kenya was among the member states that adopted the Sustainable Development Goals (SDGs) spearheaded by the United Nations under the 2030 Sustainable Development Agenda. Goal Three purposes to guarantee healthy lives and advance the well-being of all individuals. Target Seven of Goal Three of the SDGs aims to expand universal access to reproductive and sexual health services in addition to family planning by 2030 (23).

Family Planning 2020 is a worldwide partnership that promotes women and girls' rights to achieve the number of children they desire to have. This partnership aims to accelerate access to contraceptives by 2020 by a further 120 million girls and women (24). Kenya also adopted the International Conference on Population and Development (ICPD), 1994, which called for the improvement of reproductive health. The Population Policy on National Development Session Paper No 3 of 2012 was adopted from ICPD. The Session Paper presents a framework for ensuring

a high quality of life while controlling population growth. It also acknowledges the urgency to lower family planning unmet needs in order to achieve Vision 2030 (24).

Regionally, African governments including Kenya committed to set apart 15% of their annual budgets for the betterment of healthcare as stipulated in the Abuja Declaration. This is still a pipe dream in Kenya as health budgets have been below the 15% Abuja Declaration target. The combined National and County budget for health in 2013/2014 was 5.5%, 2014/2015 was 7.5%; in 2015/2016 was 7.7% and 2016/2017 was 7.6% (25). The Maputo Protocol calls for 15% budgetary allocation of the health budget for reproductive health. This is aimed to advance access to sexual and reproductive health in Africa (24). Kenya is also one of the countries implementing the "Accelerating Access to Postpartum Family Planning" (PPFP) in Asia and Sub-Saharan Africa (26). The program aims to reduce unmet needs and improve access to family planning services in postpartum women (26).

In Kenya, the rights to access the utmost achievable health including reproductive health are enshrined in the 2010 Constitution of Kenya Article 43 (2). The Reproductive Health Care Bill 2014 part two also obligates the County and National governments to guarantee the accessibility of contraceptives and family planning services. This includes counseling, information and contraceptive options (3). The Kenya Health Policy 2014-2030, aims to achieve the maximum standards of health for Kenyans as per the Constitution of Kenya, Vision 2030 and Global commitments, taking into account the role played by National and County Governments. Objective Four of the policy is to provide essential care and one of the strategies is to ensure widespread access to reproductive services (27).

Kenya launched the first National Reproductive Health Policy in 2007 which was developed to improve the reproductive health of Kenyans by ensuring rightful access to reproductive health services (24). The Kenya National Family Planning Costed Implementation Plan (CIP) 2012-2016 was developed to mobilize and focus resources so as to improve access to quality family planning services (24). The CIP 2017-2020 is currently under review so as to achieve family planning goals in an efficient and effective way. The second Kenya Health Sector Investment and Strategic Plan (KHSSP) 2013-2017, guides the National and County Governments in prioritizing health-related matters. It promotes the provision of health services including reproductive and FP services in all levels of care including Faith-Based Organizations (FBOs) and the private sector. It aimed to

increase the number of women (15-49 years) receiving family planning services from 44% in 2013 to 80% in 2017.

The Reproductive Health Commodity Security Strategy 2013-2017 was developed in line with the second KHSSP to guide management of reproductive health commodities in the country. It ensures a continuous and accessible supply of reproductive health commodities to those who require them at all times and in all health facilities. It is a review of the National Contraceptive Commodities Strategy 2007 to 2012. It lays out guidelines to ensure commodity security at all levels and reduce overstocking, spoilage and theft and any wastage of commodities (27).

The Kenya Health system has undergone a lot of transformation due to the devolution of health services in 2013. This was adopted pursuant to the Constitution inaugurated in 2010. The aim was to improve primary health services and enhance effectiveness in health delivery. The Kenya Reproductive, Maternal, Newborn, Child and Adolescent Health (RMNCAH) Investment Framework 2016, is a costed guide to improve RMNCAH services in the National and County levels of Government. It purposes to raise the contraceptive prevalence rate to 73% among married women and reduce teenage pregnancy to 11% among others. Other policies like the Elimination of User Fees for Public Health Care Services targets to advance access to family planning services at the dispensary and health center level (28).

### 2.4 The supply chain for family planning methods in Kenya

The Ministry of Health mandates the Kenya Medical Supplies Authority (KEMSA) to procure, store and distribute health commodities in various public health programmes including reproductive health. A contraceptive logistics management unit at KEMSA and Department of Reproduction Health ensure the supply chain is running effectively. The Department of Reproductive Health supervises the forecasting, quantification, and monitoring of stock levels of contraceptives and capacity building (29).

The Government of Kenya contributed about 600 million shillings annually towards the purchase of contraceptives for the financial years; 2011/2012, 2012/2013 and 2013/2014. This was directed to KEMSA for the purchase of depot medroxyprogesterone. Other contraceptives were procured through the support of agencies such as UNFPA, USAID, World Bank, DFID, and KFW. The first budgetary allocation for contraceptives was done in 2005/2006 (24,29).

After procurement through various channels, contraceptives are stored in KEMSA warehouses awaiting distribution. The contraceptives supplied to health facilities are based on needs (pull system). This is coordinated by the Logistics Management Unit (LMU) at the Ministry of Health, Reproductive Health Unit. Population Services Kenya (PS Kenya) works in conjunction with KEMSA to distribute contraceptives to private facilities. Health facilities prepare monthly consumption reports based on dispensed-to-user data from service delivery points (SDP) which are forwarded to the Sub County stores (previously district stores). The monthly contraceptive reports and Sub County stores reports are then uploaded to the DHIS2, an online platform for reporting consumption. The family planning supply chain is as presented in Figure 2-3. The LMU then accesses the system and directs KEMSA to supply the Sub County stores every quarter based on their orders. Dispensaries, health centers, and Sub County Hospitals receive drugs from the Sub County Stores every month based on their consumption reports. County Referral Hospitals (Former Provincial Hospitals) and National referral hospitals receive the contraceptives directly from KEMSA.

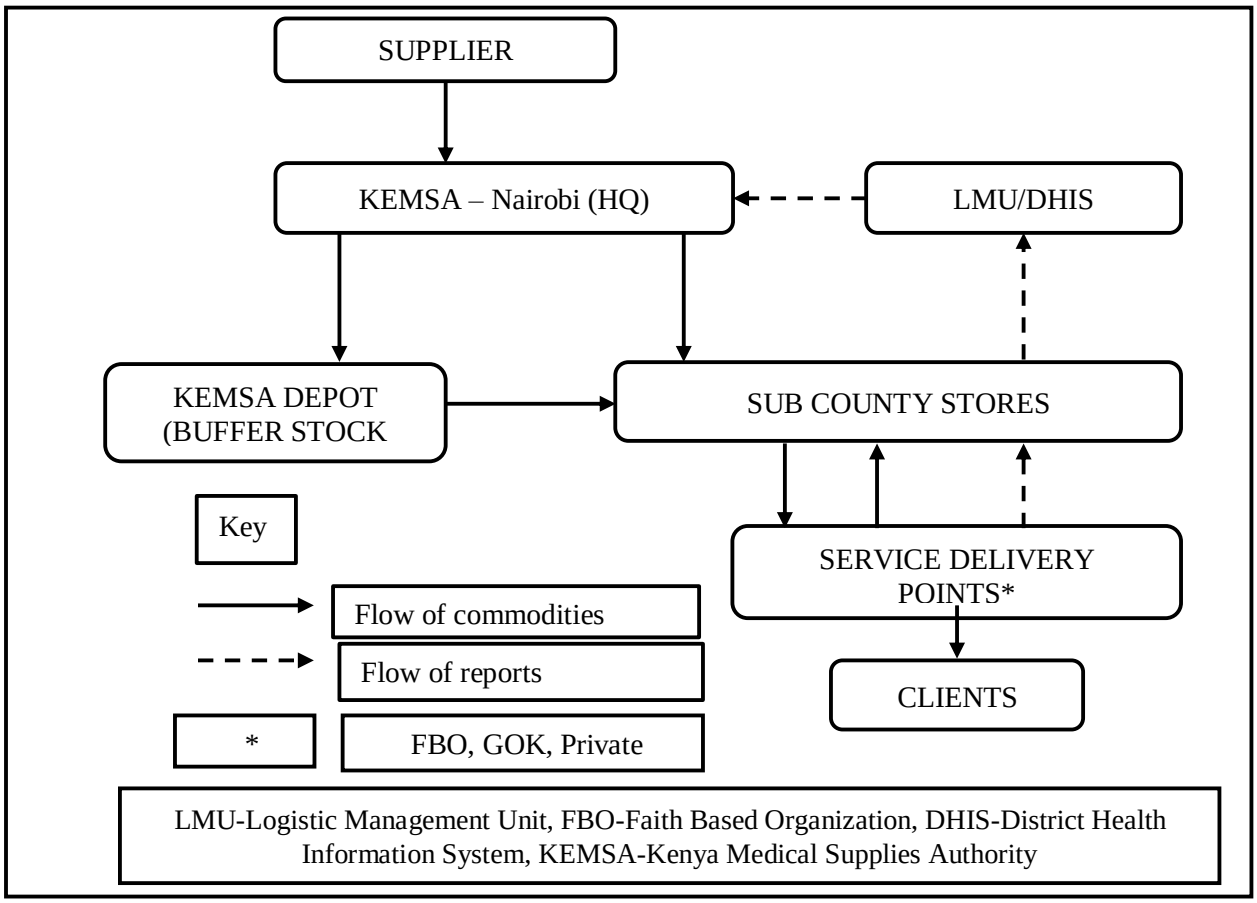



Figure 2-3: Family planning supply chain in the public sector

## 2.5 Methods of quantification of contraceptives

Two methods of quantification of contraceptives are adjusted consumption method and the patient morbidity –standard treatment methods. The patient morbidity standard treatment method quantifies the number of drugs needed by multiplying the number of drugs required for optimal treatment of a health condition by the number of treatment episodes. The adjusted consumption method uses actual consumption data from standard facilities where consumption is considered acceptable. Consumption data may also be adjusted upwards or downwards (30).

The Reproductive and Maternal Health Services Unit (RMHSU) Family Planning program carries out forecasting and quantification of contraceptives annually. The quantification exercise uses the public sector method mix as shown in Table 2-1 for the year 2014 and the projected method mix for 2018. The assumption made was that there is no major change in the use of contraceptives over the years. The method mix is derived from KDHS 2014 (31).

Table 2-1: Method mix of contraceptives

| **Type of contraceptives** | **Percentage of total** | |
|---|---|---|
| | **Method mix 2014** | **Projected method mix 2018** |
| Pills (Progestin-Only Pills ) and (Combined Oral Contraceptives) | 15.0 | 17.9 |
| Family Planning Injections | 49.5 | 44.3 |
| Intrauterine contraceptive devices | 6.4 | 5.8 |
| Implants (Jadelle® and Implanon®) | 18.6 | 29.6 |
| Sterilization by Bilateral Tubal Ligation | 6.4 | 0.5 |
| Sterilization by Vasectomy | 0.01 | 0.02 |
| Male Condoms | 4.1 | 3.9 |
| Female Condoms | 0.0 | 0.03 |

Progestin-only pills contributed 30% of the pills while Combined oral pills 70%. Each of the implants was procured equally.

The Family Planning program uses data at the central store, KEMSA; the data includes stock at hand, receipts, and issues. It also uses stock at hand at the health facilities and sub-County stores (derived from monthly reports in the DHIS2) and data on commodities that have been ordered but

not yet supplied to the central store. A Reality Check tool® (a morbidity-based forecasting tool) is used to determine quantities based on a number of sexually active women of reproductive age for the procurement period. Service point and consumption data from health facilities reports in the DHIS2 are used to validate the quantification exercise (31).

### 2.6 Review of time series studies of family planning methods in Africa.

Trends and patterns on contraceptive use studies in Africa have mainly been based on national demographic and health surveys. No study has used consumption data to evaluate changes in contraceptives use in Africa. A trend analysis of family planning services was done in Ghana evaluating the 1993, 1996 and 2002 demographic and health survey data. It showed that estrogen/progesterone pill, condoms, and injections were the most common methods offered in facilities. There was an increase in the number of family methods offered; however, there was a decline in the availability of contraceptives between 1996 and 2002 (32).

A subnational analysis of trends in contraceptive use in Ethiopia evaluated data obtained from national demographic and health surveys done in 2000, 2005 and 2011. It showed an upsurge in modern contraceptives uses over the years. Injectables were the most frequently used contraceptives trailed by implants and pills. There was also a decrease in the total fertility rate between 2000 and 2011 (33).

A study done to evaluate patterns of contraceptive use in adolescents evaluated demographic and health survey data from Burkina Faso (2003 & 2010), Ethiopia (2000, 2005 & 2011 and Nigeria (2003, 2008 & 2013). The prevalence of use of contraceptives in adolescents in the three countries was generally low with the highest being among those in the union. There was a significant rise in the number of adolescents using modern contraceptives during the period unlike in Nigeria and Burkina Faso where there was no progress (34).

A study on the stall in fertility decline in Eastern Africa evaluated data from four demographic and health surveys before 2007 in Kenya, Tanzania, Zimbabwe, and Uganda. It showed a general stall or decline in fertility rates across three regions. In Kenya and Tanzania, fertility decline had stalled among married women. There was a decline in fertility in Uganda among educated women while in Zimbabwe there was a stall among women with lower than secondary education (34).

# CHAPTER THREE: MATERIALS AND METHODS

## 3.1 Study design and study population

The study design was a time series analysis of family planning data. The target population was women aged between 15 and 49 years using contraceptives in Kenya. The study population was Kenyan women of ages from 15 to 49 years using contraceptives in the public sector and faith-based organizations whose consumption was reported through the DHIS2 from 2014 to June 2018.

## 3.2 Study setting

Aggregate data on the use of contraceptives in Kenya public sector was collected from DHIS2. This was the online reporting platform for health data which included contraceptives consumption and service delivery point data. It captured data from Government health facilities (GOK), Faith Based Organization (FBO) health facilities and private clinics that received contraceptives supplied by the government through KEMSA. The study utilized data on dispensed products from the Facility Contraceptive Consumption Report and Request form and MOH 711 Integrated Summary Report (Reproductive and Child Health, Medical and Rehabilitation services) for service point data for pills, implants, IUCDs, and injectables. The MOH 711 Integrated Summary Report contained the number of clients that received each type of contraceptive. The Facility Contraceptive Consumption Report and Request form contained beginning balances, receipts, issues (dispensed), ending balances, and requested quantities for all contraceptives in each health facility. This study utilized dispensed data.

## 3.3 Sampling and inclusion criteria

This study utilized the universal sampling method. All consumption data from health facilities which were reported through the DHIS2 were included. The four most commonly used modern contraceptive methods according to the KDHS were included and these were injectables, implants, pills, and intrauterine contraceptive devices. Devices or medicines were included if they were exclusively used for contraception and if they were hormonal based, therefore condoms and vaginal devices were excluded. Surgical methods for contraception, like tubal ligation, were also excluded.

## 3.4 Data collection and Management

Consumption and service point data of implants, IUCDs, pills, and injectables were extracted from DHIS2 for the years 2014, 2015, 2016 & 2017. To improve forecasting, data cleaning and

transformation was done. This helped in mitigating incomplete and inconsistent data sets. Equation 1 was applied to data whose reporting rate was less than 100% to correct for underreporting. Reporting rate represented the number of reports uploaded versus those expected in the country of which the ideal reporting rate was 100%.

**Equation 1: Equation for adjusting the consumption of contraceptives to correct for under-reporting**

$$Adjusted\ consumption = \frac{Consumption\ \times 100\%}{Reporting\ rate}$$

Equation 1 was also applied when adjusting the service point data so as to reflect a 100% reporting rate. In this case, consumption was replaced with service point data.

### 3.5 Data analysis

Data analysis of the contraceptives consumption data was done using the R software, version 3.4.3.

#### 3.5.1 Exploratory analysis

A time series graph was plotted for each of the commodities. Visual inspection of the graph was done to check for trend, stationarity, and seasonality. The augmented Dickey-Fuller test was also conducted to test for stationarity. For non-stationary series, differencing was done to transform it to stationarity. The Auto-Correlation Function (ACF) and the partial ACF graph was plotted as well as the Ljung-Box test to test for the presence of autocorrelation. The data were log transformed to remove any autocorrelation and to ensure the consumption data fitted with an additive model.

The time series was then decomposed into its constituent components, which were the seasonal, random, and trend components. For seasonal data, decomposition was done using the "*decompose* ()" function in R software which separated the time series into the trend, seasonal, cyclic and random components. Each of the contraceptives trend and seasonal components were plotted separately and described. The data sets were tested for seasonality using a correlogram or ACF and partial ACF plot where the autocorrelation coefficient showed a pattern, then a seasonal pattern was assumed.

Contraceptives consumption (implants, IUCDs and Injectables) and service point data was checked for similarity using the time series correlation method. A scatter plot of the consumption and service data was plotted and a trend line fitted to visualize any similarities.

### 3.5.2 Forecasting of consumption data

A short-term forecast for demand for contraceptives was done using exponential smoothing with underlying state space models and Autoregressive Integrated Moving Average (ARIMA) methodologies and their predictive accuracies were compared.

#### 3.5.2.1 Exponential smoothing methods with underlying state space models

Forecasting using exponential smoothing methods was done using the "*ets*" function in R. The "*ets*" function returns a model with three characters "ETS" where E denotes the type of errors present, T denotes the type of trend while S denotes the season type. The types of errors, trends and seasons are described as "N" for none, "M" for multiplicative, "A" for additive and "Z" for automatically selected. The forecast was done for six months (h =6). The 80 and 95% prediction interval for the forecast was computed and plotted for each of the exponential smoothing methods. The forecast errors for the consumption data (training data) and validation data (test data) were also determined.

The general equation for exponential smoothing is as shown in equation 2

Equation 2: General equation for exponential smoothing

$$\boldsymbol{X_{n+1} = X_n + \alpha(1-\alpha)\, X_{n-1} + \alpha(1-\alpha)^2 X_{n-2} + \cdots = X_n + (1-\alpha)\widehat{X}_n}$$

Where

$\alpha =$ is a smoothing parameter, a value which lies between -1 and +1.

n= number of observations

$\hat{X}$ = mean of observations

$X_n$= the actual consumption value at the n observation

#### 3.5.2.2 Forecasting using ARIMA models

Autoregressive Integrated Moving Average (ARIMA) p, d, q models were developed. p was the degree of autocorrelation, d as the order of differencing and q was the degree of moving averages was fitted. Non-stationary data was differenced "d" times to make it stationary.

Both stepwise and non-stepwise methods were used to determine the best models. A correlogram (ACF plot) and partial correlogram (PACF) were then plotted to determine the appropriate values for p (value from partial autocorrelation) and q (value from autocorrelation) in the ARIMA model. Once the best model was selected, parameters of the ARIMA model were estimated and used as a predictive model to make forecasts for future contraceptives consumption. The parameters of the ARIMA (p, d, q) model were also projected using the "*auto. Arima*" function (35). The *auto. Arima* function is an algorithm that tries all possible parameters (p, d, q) within the set constraints and chooses the best model for the data. The selected model is one that has the lowest Bayesian Information Criteria (BIC) and Akaike Information Criteria (AIC) and with corresponding in sample errors (36). The mathematical model is presented in Equation 3.

**Equation 3: Mathematical model for Autoregressive Integrated Moving Average Method**

$$W_t = \mu + \sum \Psi_i\,(\mathrm{B}) X_{i,t} + \theta(B)/\varphi(B)\varepsilon_t$$

Where: t= indexes time,

B= is the back shift operator, that is $BX_t = BX_{t-1}$,

$W_t$= is the response series or difference of response series,

$\phi(B) =$ is the auto regressive operator,

μ = the constant term,

$\theta(B)$ = the moving average operator, $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$,

$X_{i,t} =$ the ith input time series or a difference of the ith input time series at time t,

$\Psi_i(B) =$ is the transfer function for the ith input series modelled as the ratio of polynomials.

$\varepsilon_t$ =random shock,

p = degree of autoregressive part

q = degree of moving average part

### 3.5.3 Cross-validation and comparison of forecasting models

The reported data for all commodities from January to June 2018 (test data) was used to validate the forecasting models. These were done by comparing the data with the point forecasts for the same period. This was done to determine how well the models forecasted the family planning consumption data

The sum of squared errors for the sample forecast errors for each method was calculated. The Ljung-Box test was used to check for non-zero autocorrelations in forecast errors. The Shapiro Wilk test was used to test for normal distribution of residuals. Fit parameters, R-square, Akaike Information Criterion (AIC), normalized Bayesian Information Criteria (BIC) were used to compare the forecasting models. Root Mean Squared Error (RMSE), Mean Absolute Scale Error (MASE), and Mean Absolute Percentage Error (MAPE) were used to quantify the forecasting errors. The R- Software scripts used for the analysis of the contraceptives are attached in Appendix A.

## 3.6 Study limitations

The study utilized secondary data from DHIS and the accuracy of the data from the primary facilities could not be verified, however, the consumption was adjusted to correct for underreporting. The forecasting of consumption was also done without taking into consideration the changes in population density.

## 3.7 Data approval and ethical considerations

Approval to use the DHIS2 data for contraceptives was sought from the Health Information Systems unit, Health Care Financing, Policy, and Planning department in the Ministry of Health. The study utilized aggregate data with no unique identifiers for clients, therefore, it was a minimal risk study. However, approval to carry out the study was sought from the Kenyatta National Hospital/University of Nairobi Ethics and Research Committee (KNH/UoN/ERC). The ethics approval was given on 5$^{th}$ March 2018 and the reference number was P714/12/2017. The approval letter is attached in Appendix B.

# CHAPTER FOUR: ANALYSIS AND RESULTS

## 4.1 Description of the dataset

The consumption and service point data used in this study was obtained from the DHIS after obtaining permission from the Ministry of Health, Kenya. The data on the consumption of Progestin-Only Pills (POP), Combined Oral Contraceptives (COC) injectables, Intrauterine Contraceptive Devices (IUCDs) and one and two-rod implants were obtained. The monthly data obtained was as reported by health facilities in Kenya and covered a period of four and a half years from 2014 to June 2018. The consumption data from January 2014 to December 2017 was used as the training data set while data from January 2018 to June 2018 was used as the test data set for validation of the forecasting models.

The consumption data represented the dispensed commodities while service point data represented the number of clients who received each of the commodities. The consumption data was extracted from the Facility Contraceptive Consumption Report and Request form while the service point data was extracted from the MoH 711 Integrated Summary Report (Reproductive and Child Health, Medical and Rehabilitation Services). The data sets were collected on 22$^{nd}$ May 2018 for the training data and 9$^{th}$ August 2018 for the validation data.

The raw data was cleaned and adjusted for reporting rate. The actual consumption was transformed to reflect a 100% reporting rate for each month by applying Equation 1 on the methods chapter. The summary of the raw data for consumption and service point data is for contraceptives attached in Appendix C and D respectively.

### 4.1.1 Summary analysis and the overall trend in consumption and service point data

The yearly mean of consumption of FP commodities and service statistics is presented in Table 4-1.

Table 4-1: Mean yearly consumption and service point statistics

| Contraceptives | Mean yearly consumption | | Mean yearly service statistics (Number of clients) |
|---|---|---|---|
| COCs | 1,914,683 | Cycles | 673,088 |
| POPs | 443,194 | | 208,479 |
| Injectables | 4,171,779 | Vials | 3,457,090 |
| IUCDs | 465,352 | Pieces | 219,051 |
| One rod Implants | 723,308 | | 610,627 |

COC-Combined Oral Contraceptives, POP- Progestin-Only Pills, IUCDs-Intrauterine Contraceptive Devices.

From Table 4-1, most women seeking family planning services used injectables followed by combined oral contraceptives, implants, intrauterine contraceptive devices and lastly progestin-only pills.

### 4.1.2 Yearly changes in product mix

The yearly changes in the product mix of family commodities were computed using the service data by dividing the number of clients using a specific contraceptive with the total number of clients using the contraceptives in that year. The total percentage was computed by diving the total number of women per year by the overall number of women seeking services from 2014 to 2017. The findings are presented in Table 4-2.

Table 4-2: Yearly proportion of women using various contraceptives from 2014 to 2017

| The proportion of women who received each family planning commodity (%) | | | | | |
|---|---|---|---|---|---|
| **Year** | **Combined oral contraceptives** | **Progestin-only pills** | **Injectables** | **Implants** | **Intrauterine contraceptive devices** |
| 2014 | 14.7 | 3.5 | 69.9 | 9.1 | 2.8 |
| 2015 | 14.1 | 3.9 | 67.3 | 11.7 | 2.9 |
| 2016 | 12.7 | 4.6 | 64.8 | 12.4 | 5.5 |
| 2017 | 9.1 | 4.4 | 64.1 | 15.5 | 6.9 |

The yearly percentage of women on combined oral contraceptives and injectables declined from 2014 to 2017 while those on implants and intrauterine devices increased. The proportion of women

who received progestin-only pills increased from 3.5 % in 2014 to 4.6% in 2016 but declined to 4.4 % in 2017. The proportion of women who had implants and intrauterine contraceptive devices increased during the study period as presented in Table 4-2. The total proportion of women seeking family planning services also decreased from 2014 to 2017 as presented in Table 4-2.

### 4.1.3 Yearly trends in the use of contraceptives from 2014 to 2017

The proportion of contraceptives consumed from 2014 to 2017 was calculated by dividing each year's consumption with the overall total for the period and represented in Figure 4-1.

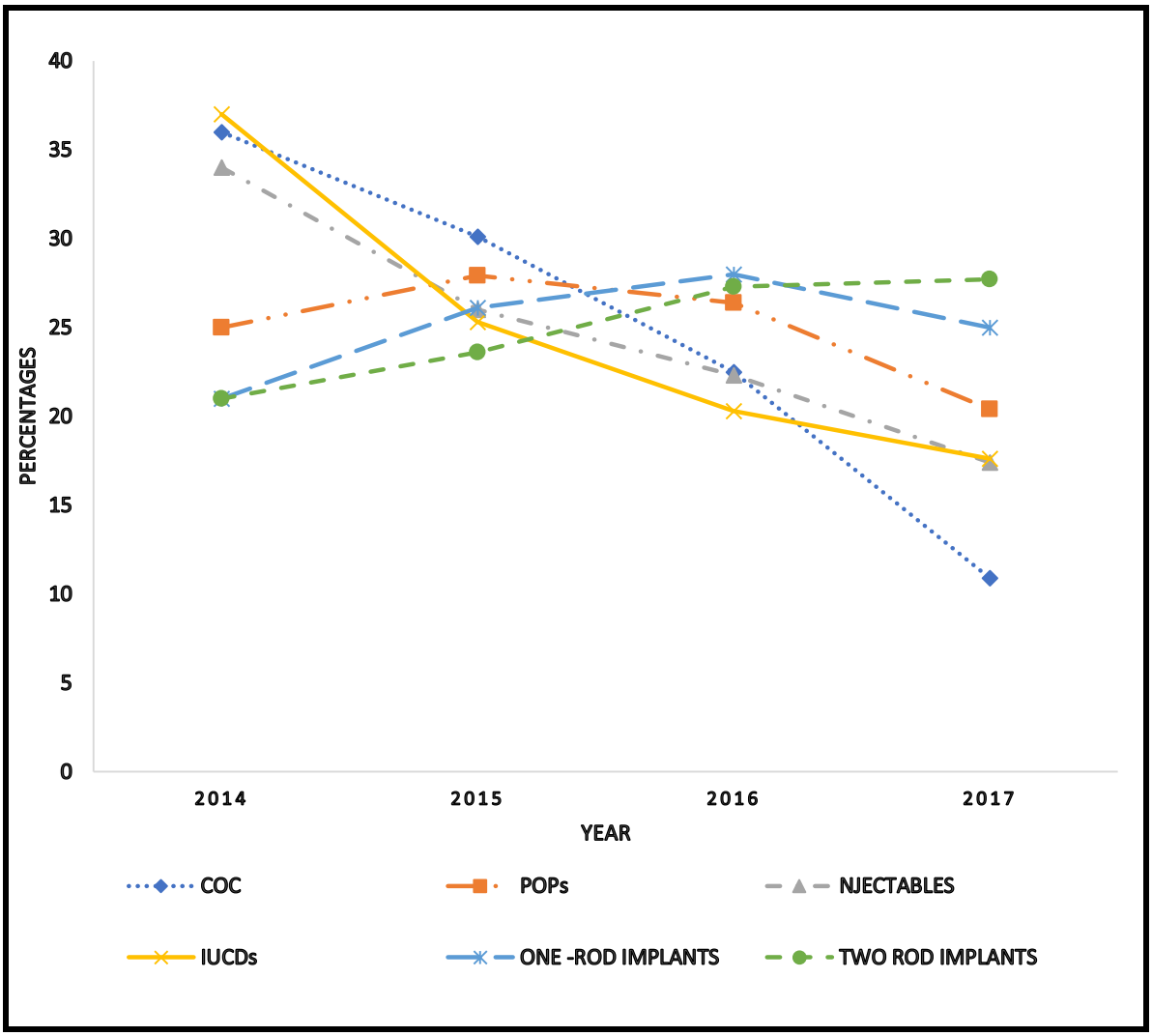



Figure 4-1: Trend in use of contraceptives from 2014 to 2017

From Figure 4-1 the proportion of COCs, injectables, and IUCDs consumed declined from 2014 to 2017 while those of two-rod implants increased. The consumption of POPs increased from 2014 to 2015 then decreased in 2016 and 2017. The consumption of one-rod implants increased from 2014 to 2016 but decreased in 2017.

## 4.2 Exploratory analysis of the contraceptives and service point data

The time series plots of COC's, POPs, Injectables consumption (Figure 4-2 a, c, and e) showed a decline in consumption from 2014 to 2017. The lowest consumption of these commodities was in July and August 2017. The consumption of combined oral contraceptives (Figure 4-2 a) had two peaks of high consumption in April 2014 and January 2015. The lowest consumption for COCs was noted in December 2016 and August 2017. The highest consumption of POP (Figure 4-2 c) was in August and October 2015 and the lowest consumption for POPs was in July 2017. The highest consumption for injectables was in February 2014, towards the end of 2016 and 2017 while the lowest was in mid-2017 as seen in Figure 4-2 (e). The service point consumption of COCs, POP, and Injectables also decreased from 2014 to 2017 (Figure 4-2 b, c, and f) respectively.

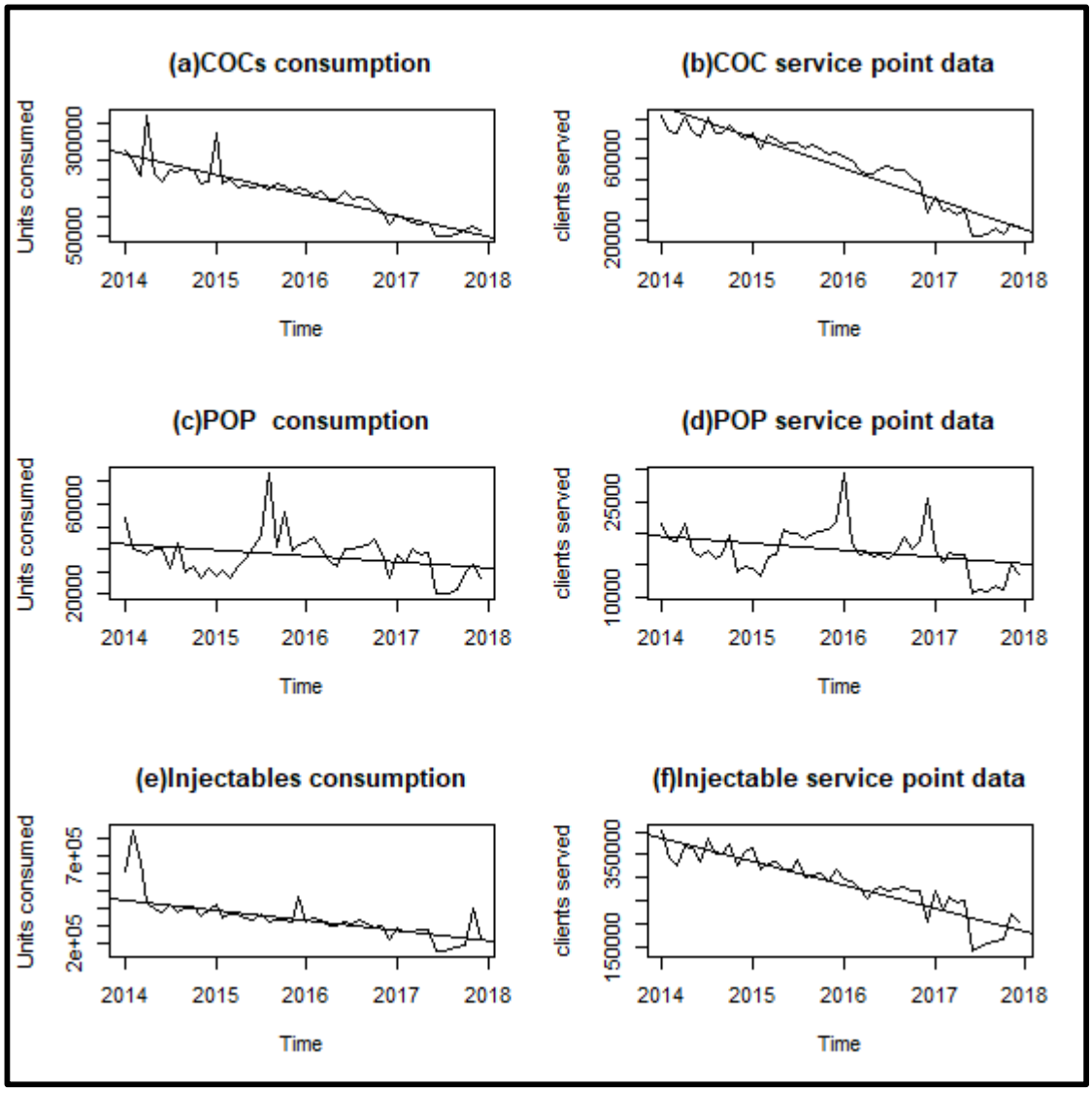



Figure 4-2: Trends in consumption data and service data for POPS, COCs, and injectables

There was increased consumption from mid-year to the end of 2014 and early 2017 for IUCDs (Figure 4-3 a) and the lowest consumption was in late 2017. One and two-rod implants had an increasing consumption from 2014 to 2017. The lowest consumption was in June 2017. The service point consumption for IUCDs decreased from 2014 to 2017 while that of implants was erratic and showed a slight increase in the same period.

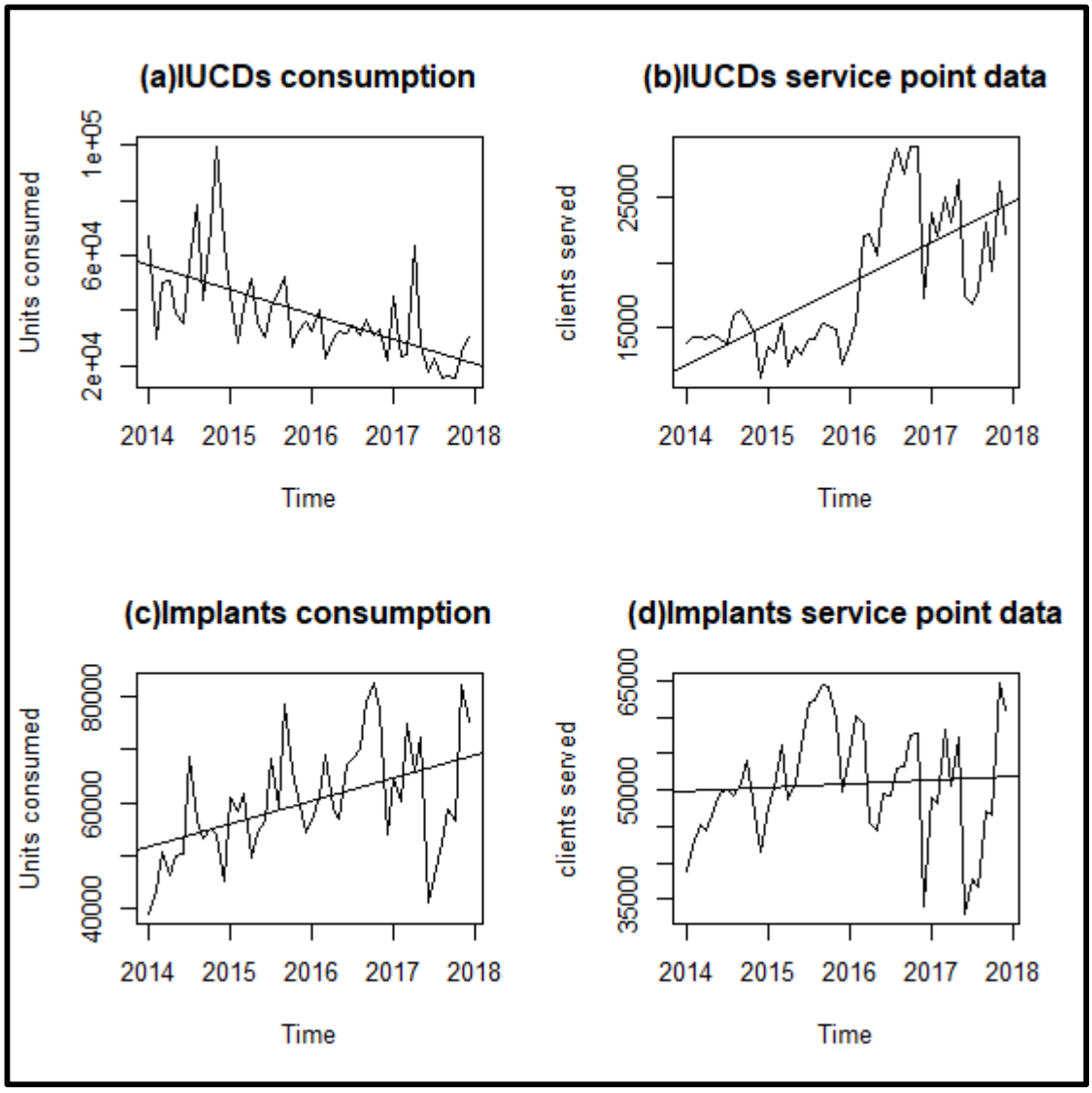


Figure 4-3: Time plots for consumption and service data for IUCDs and implants

### 4.2.1 Evaluation of the trends in consumption of contraceptives.

The consumption time series of each family planning commodity was decomposed using the moving average method to its seasonal, trend and random components. The trend component for each of the time series is presented in Figure 4-4.

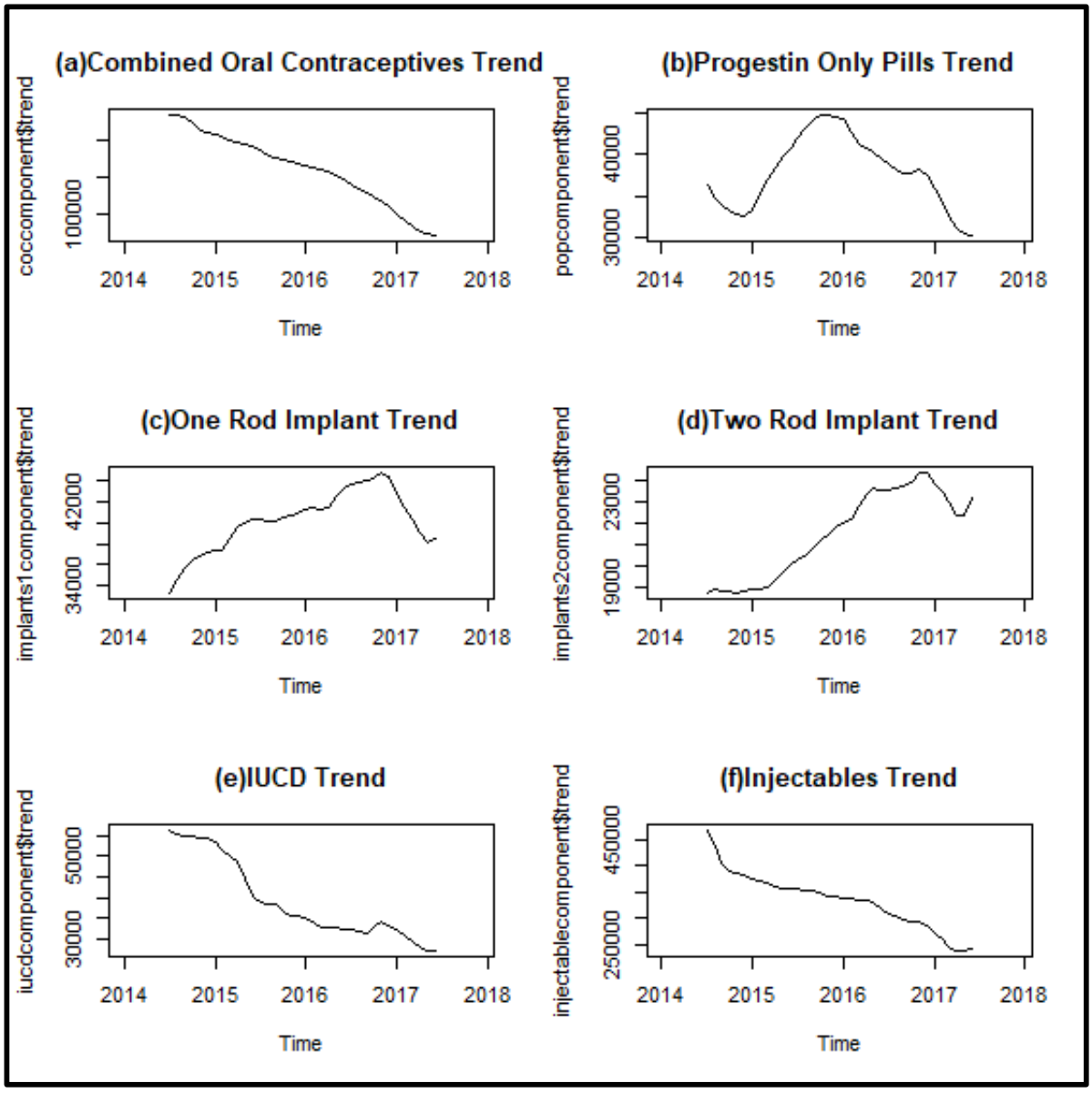



Figure 4-4: The trend component in the consumption of each contraceptive

The consumption of IUCDs, injectables and combined oral contraceptives has been on the decline since 2014. For implants and POPs, there was an increase in consumption followed by a decline. The consumption of COCs showed a declining linear trend.

### 4.2.2 Seasonal patterns in the consumption of contraceptives.

The time series plots of the contraceptives were examined for seasonality by plotting the seasonal components after decomposition of the time series (Figure 4-5). The seasonal indices were determined and are attached in Appendix E. The consumption of contraceptives had seasonal variations with periods of high and low consumption.

The consumption for combined oral contraceptives was the highest consumption in January; other high periods were in September and October. The lowest periods of consumption were in April, November, and December. The progestin-only pills had the highest periods of consumption in August and October while the lowest consumption was in December The one-rod implants had the highest consumption in July and the lowest consumption was in June and December. The two-rod implants had the highest consumption in March and September while the lowest consumption was in June and December.

The injectables had the highest consumption in January and December while the lowest was in June and August. For intrauterine contraceptive devices, the highest consumption was in April, August, and November while the lowest was in February and June.

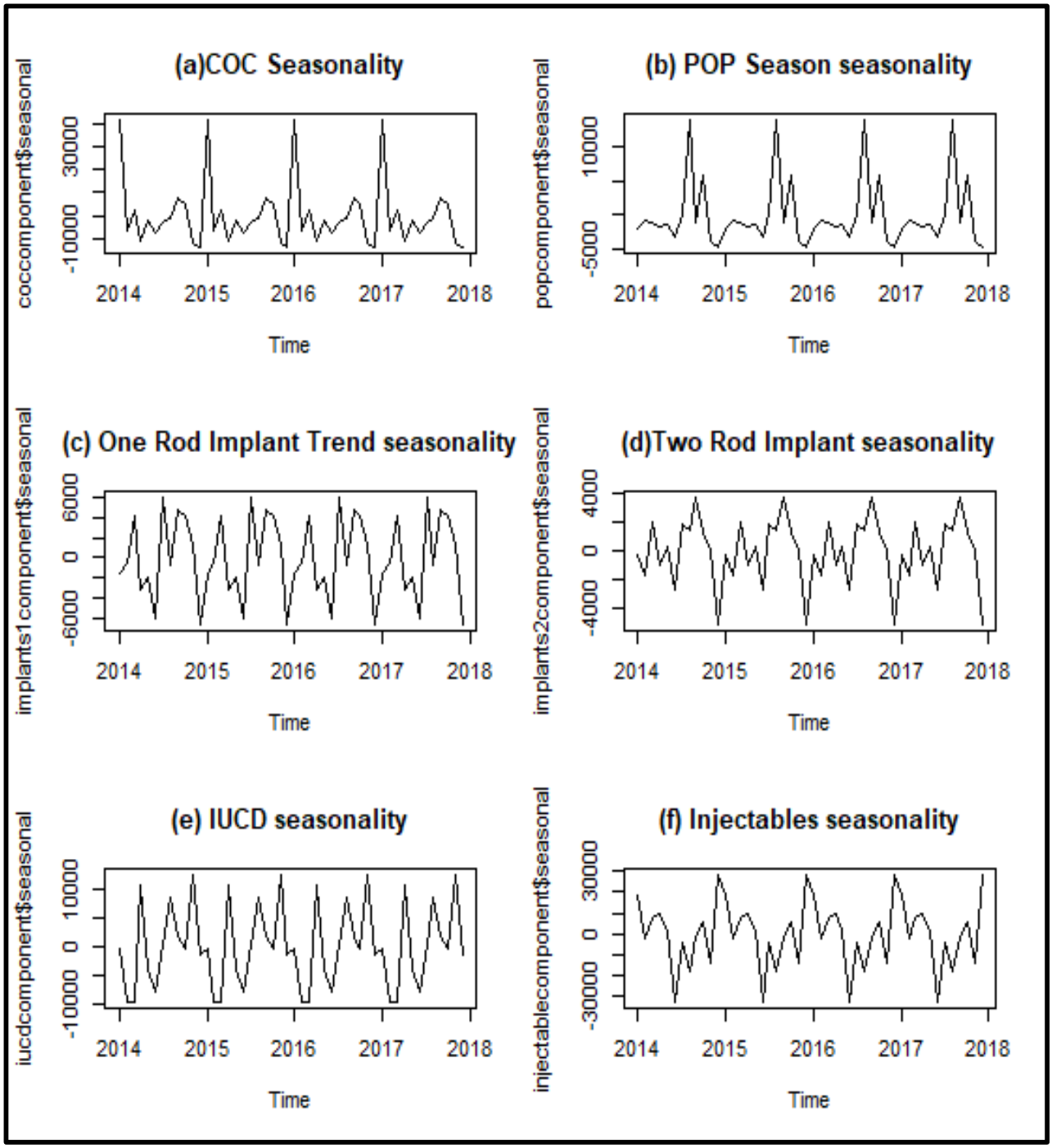



Figure 4-5: Seasonal components of the consumption of each contraceptive in Kenya between 2014 and 2017.

### 4.3 Comparison of service point data and consumption data of contraceptives.

To compare consumption data and service point data, time series for injectables, intrauterine contraceptive devices, and implants were plotted side by side as presented in Figure 4-6.

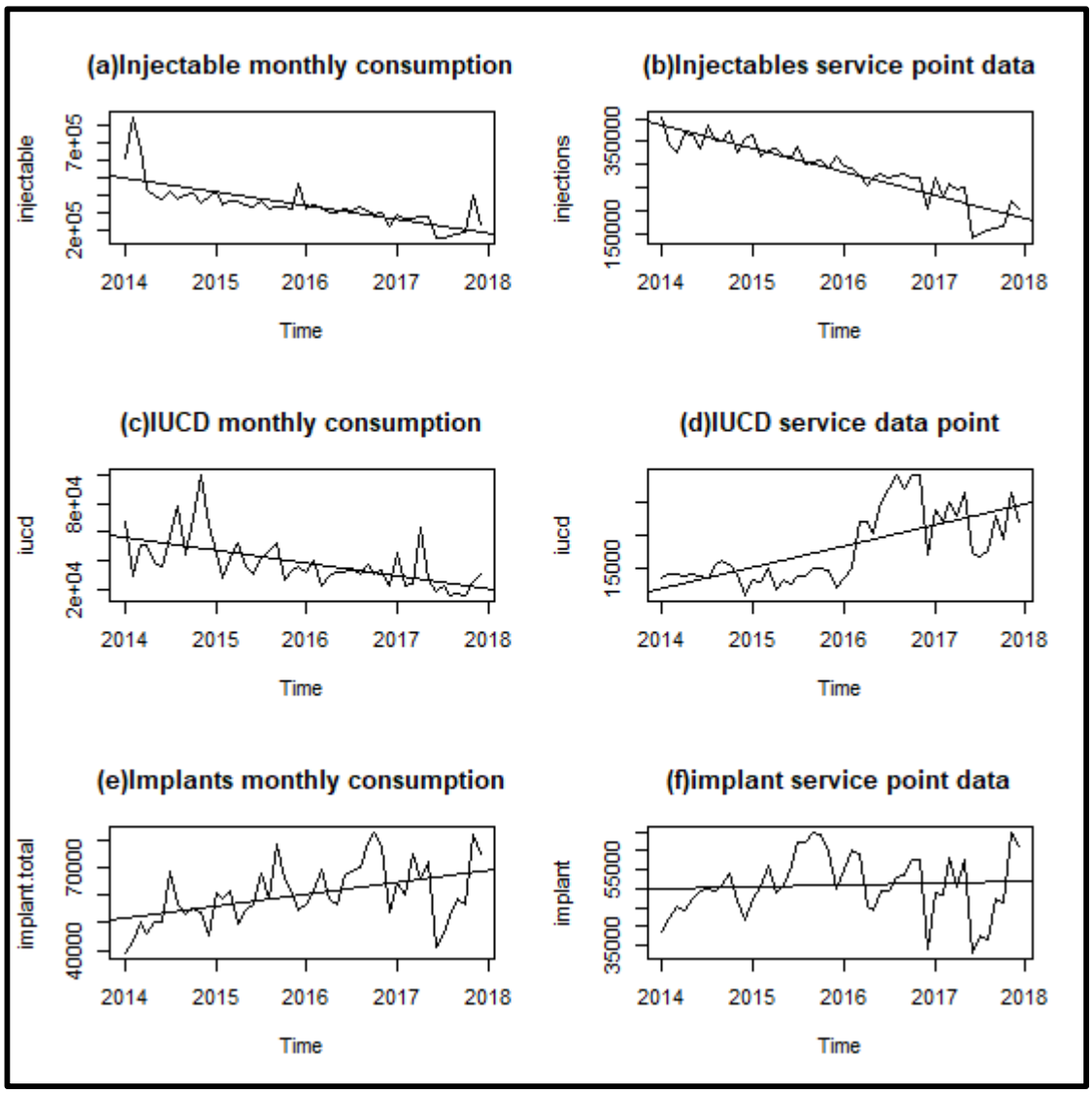
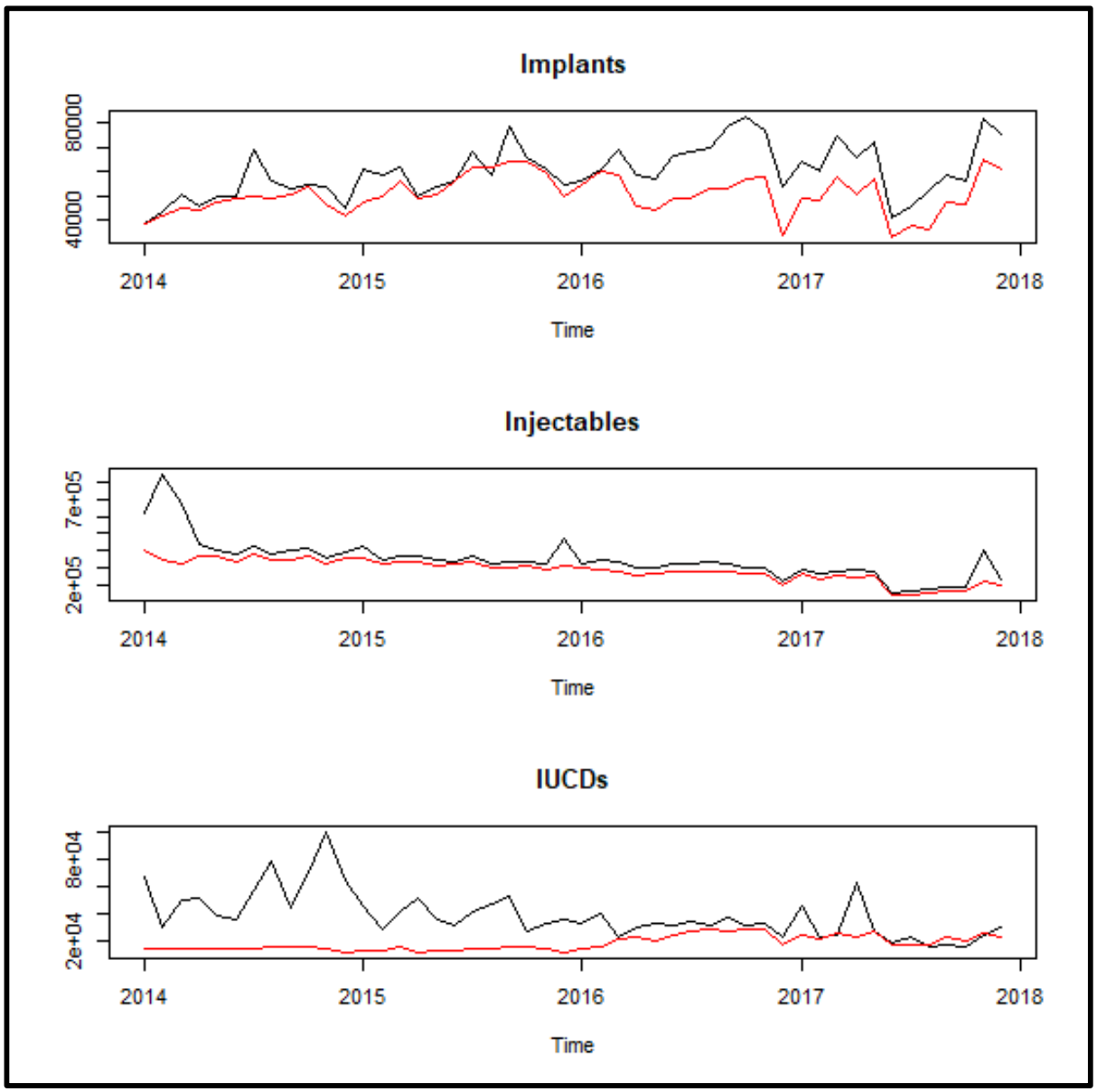



Figure 4-6: Comparison between consumption and service point data of injectables, IUCDs, and implants

The trends of the consumption and service point data for injectables were both declining. The trend in the consumption of implants was increasing while that of service point data increased slightly. The trends for intrauterine contraceptives devices for consumption and service point data were different. The service point data plot for IUCDs was increasing (Figure 4-6 a) while that of

consumption data (Figure 4-6 b) was decreasing across the years. The trends for consumption data and service data for injectables, IUCDs, and implants were further plotted on the same graph to check for any similarities.




Key- Black represents consumption data while red represents the service point data

Figure 4-7: Comparison of service and consumption data of implants, IUCDs, and injectables

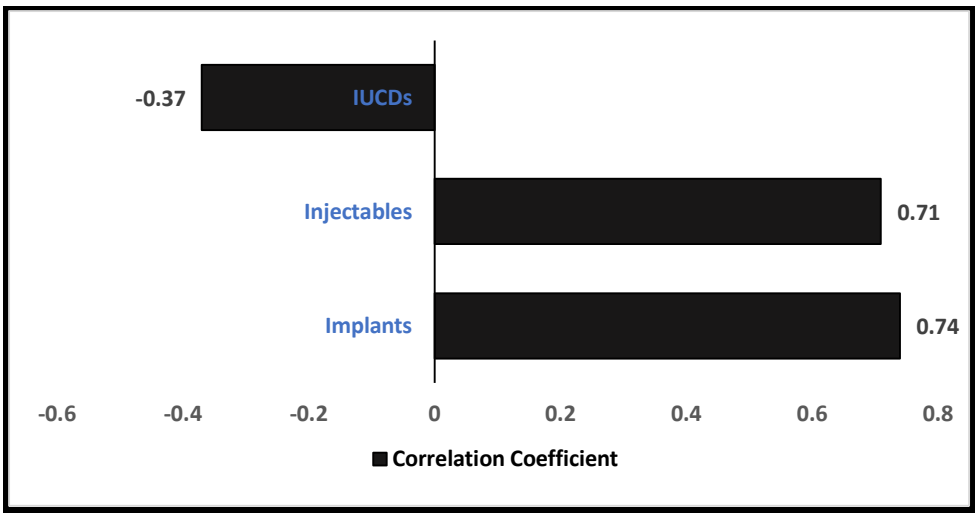



Figure 4-8: Correlation coefficients between consumption data and service data of implants, injectables, and IUCDs

Figure 4-8 shows that the reported service point data and consumption for implants and injectables were closely related while those of IUCDs were not. This could indicate a gap in reporting either over or under-reporting of the service point data or consumption data at the facilities.

### 4.4 Autoregressive Integrated Moving Average (ARIMA) modeling and forecasting

The family planning data were first log-transformed to minimize autocorrelation. The plot of the log-transformed data is attached in Appendix F. The log-transformed data were once differenced to remove the trend. The differenced data set was then plotted to determine if it was stationary. In addition, the augmented Dickey-Fuller test for stationarity was conducted. A second differencing procedure was conducted for data that were not stationary. Plots of differenced data are attached in Appendix G. The plots of the transformed (differenced and logged) data are presented in Appendix H.

Identification of the ideal model for each of the family planning data was done manually and using the "*auto. arima*" function in the forecasting package of R. In the manual method, the PACF and ACF plots of the differenced series were examined for cut off, gradual decay and seasonal patterns. These were used to determine the orders of the ARIMA models. The "*auto. arima*" function was executed using two different extensions "*stepwise*" and "*non-stepwise*". The latter is known to give the best models.

Table 4-3 shows the various model parameters for each family planning commodity using the ARIMA stepwise and non-stepwise methods. The model that had the lowest Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) was selected for forecasting.

Table 4-3: Model parameters for ARIMA using the stepwise and non-stepwise Method

| Contraceptives | METHOD | MODEL | AIC | AICc | BIC |
|---|---|---|---|---|---|
| POP | Stepwise | ARIMA(1,1,0) | -15 | -14.72 | -11.3 |
| | Non-stepwise | ARIMA(1,1,0) | -15 | -14.72 | -11.3 |
| COC | Stepwise | ARIMA(0,1,1) with drift | -17.5 | -17.01 | -12.02 |
| | Non-stepwise | ARIMA (0,1,1)with drift | -17.5 | -17.01 | -12.02 |
| One rod Implant | Stepwise | ARIMA (0,1,1) | -26.17 | -25.9 | -22.47 |
| | Non- stepwise | ARIMA(1,1,3) | -32.26 | -30.8 | -23.01 |
| Two rod Implant | Stepwise | ARIMA (0,1,1) | -32.37 | -32.1 | -28.67 |
| | Non stepwise | ARIMA(0,1,1) | -32.37 | -32.1 | -28.67 |
| IUCDs | Stepwise | ARIMA (2,1,0) | 37.51 | 38.07 | 43.06 |
| | Non stepwise | ARIMA(0,1,1) | 35.91 | 36.18 | 39.61 |
| Injectables | Stepwise | ARIMA(0,1,1) | -13.42 | -13.14 | -9.72 |
| | Non stepwise | ARIMA(5,1,0) with drift | -18.15 | -15.27 | -5.2 |

From Table 4-3, progestin-only pills, combined oral contraceptives and two-rod implants had similar model parameters for both stepwise and non-stepwise methods. For one rod implants, IUCDs and injectables, model parameters differed with the method used for parameter estimation. The non-stepwise method gave the best fit model based on low BIC and AIC values.

### 4.4.1 Model diagnostics for ARIMA models

The residuals of the selected models were checked for normal distribution and autocorrelation using the Shapiro Wilk test and Ljung Box test respectively as shown in Table 4-4. The fit statistics for the data set from 2014 to 2017 (training set) were generated and are attached in Appendix I. The consumption of the contraceptives was forecasted for six months using the ARIMA models. The point forecasts and the forecast intervals for the six months are attached in Appendix J. The actual consumption from January to June 2018 was used to validate the forecasts. The out of sample fit statistics for the forecasts are attached in Table 4-4.

Table 4-4: Out of Sample Fit Statistics for the Selected Models

| OUT OF SAMPLE PARAMETERS | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **MODEL** | **ME** | **RMSE** | **MAE** | **MPE** | **MAPE** | **ACF1** | **Theil's U** |
| POP | ARIMA(0,1,1) | -0.1090 | 0.1149 | 0.1090 | -1.0732 | 1.0732 | 0.2653 | 3.0732 |
| | ETS (M,N,N) | -0.0916 | 0.0994 | 0.0916 | -0.9021 | 0.9021 | 0.2301 | 2.7389 |
| COC | ARIMA(1,1,0) with drift | 0.3047 | 0.3697 | 0.3047 | 2.6960 | 2.6960 | 0.5805 | 2.6173 |
| | ETS (A,N,N) | 0.1356 | 0.2119 | 0.1572 | 1.1911 | 1.3870 | 0.5356 | 1.5107 |
| IUCD | ARIMA(0,1,1) | -0.0541 | 0.2877 | 0.2492 | -0.6212 | 2.4953 | 0.2667 | 0.9111 |
| | ETS(M,N,N | -0.0545 | 0.2877 | 0.2492 | -0.6248 | 2.4954 | 0.2667 | 0.9120 |
| Injectables | ARIMA(5,1,0) with drift | 0.2378 | 0.2886 | 0.2378 | 1.9283 | 1.9283 | 0.1245 | 3.6623 |
| | ETS(A,N,N) | -0.1169 | 0.1280 | 0.1169 | -0.9489 | 0.9489 | -0.3002 | 1.5550 |
| One rod Implants | ARIMA(1,1,3) | 0.0479 | 0.0659 | 0.0590 | 0.4472 | 0.5525 | -0.3542 | 0.7018 |
| | ETS M,N,N | -0.0647 | 0.0899 | 0.0717 | -0.6110 | 0.6756 | -0.3747 | 1.0209 |
| Two rod Implants | ARIMA(0,1,1) | 0.0931 | 0.1033 | 0.0931 | 0.9097 | 0.9097 | -0.0609 | 1.3916 |
| | ETS(A,A,N) | 0.0515 | 0.0677 | 0.0515 | 0.5023 | 0.5023 | -0.2357 | 0.8018 |

Table 4-5: Test for normal distribution and autocorrelation of residuals for ARIMA models for the consumption of contraceptives.

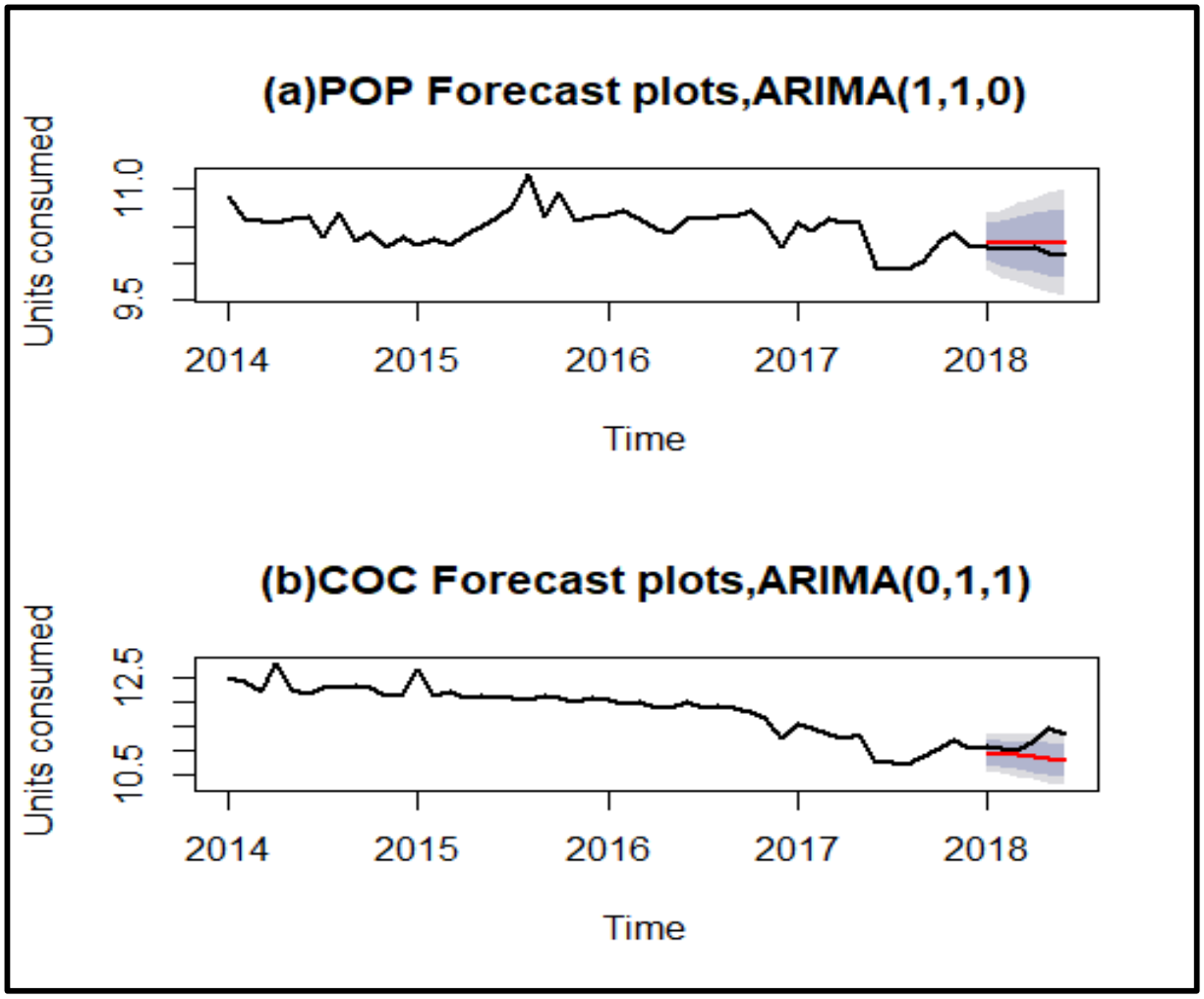
| FP COMMODITY | MODEL | SHAPIRO WILK TEST (p-value) | Augmented Dickey Fuller Test(p-value) |
|---|---|---|---|
| POP | ARIMA(1,1,0) | 0.285 | 0.649 |
| COC | ARIMA(0,1,1) with drift | 0.002 | 0.919 |
| IUCD | ARIMA(0,1,1) | 0.961 | 0.749 |
| INJECTABLE | ARIMA(5,0,1) with drift | 0.003 | 0.493 |
| ONE ROD IMPLANT | ARIMA(1,1,3 | 0.161 | 0.599 |
| TWO ROD IMPLANT | ARIMA(0,1,1) | 0.009 | 0.415 |

From Table 4-5, the residuals of the selected models were normally distributed except for combined oral contraceptives. The residuals of the selected models for contraceptives were not autocorrelated. ACF and PACF of the residuals were also plotted and are attached in Appendices K and L.

### 4.4.2 Validation of the ARIMA models

Actual consumption of contraceptives from January to June 2018 was used to test the validity of the forecasting models. Comparison between the forecasts and actual consumption were made. The forecasting residuals were also overlaid over the actual consumption as shown in Appendix M.

For progestin-only pills (Figure 4-9 a), the predicted mean consumption data were consistently greater than the actual consumption in 2018. The actual consumption data was within the 95% confidence interval. The prediction error was largest after about three forecasts. The forecasts did not reflect a decline in consumption. For combined oral contraceptives (Figure 4-9 b), the predicted mean consumption was consistently lower than the actual consumption during the forecasting period. The forecasts did not reflect the increase in consumption of combined oral contraceptives towards May 2018 but it was within the 95% prediction interval.




Key: Black line- the actual consumption and red line –predicted consumption
Figure 4-9: Comparison between forecasts and actual data for progestin-only pills and combined oral contraceptives.

For one rod implants (Figure 4-10 a), the mean average forecasts were consistently slightly lower than the actual consumption but still within the 95% forecast interval. The forecast reflected the increase in actual consumption during the forecast period. For two rod implants (Figure 4-10 b), the forecasts were consistently lower than the actual consumption. The forecast did not reflect an increase in consumption from March to May 2018.

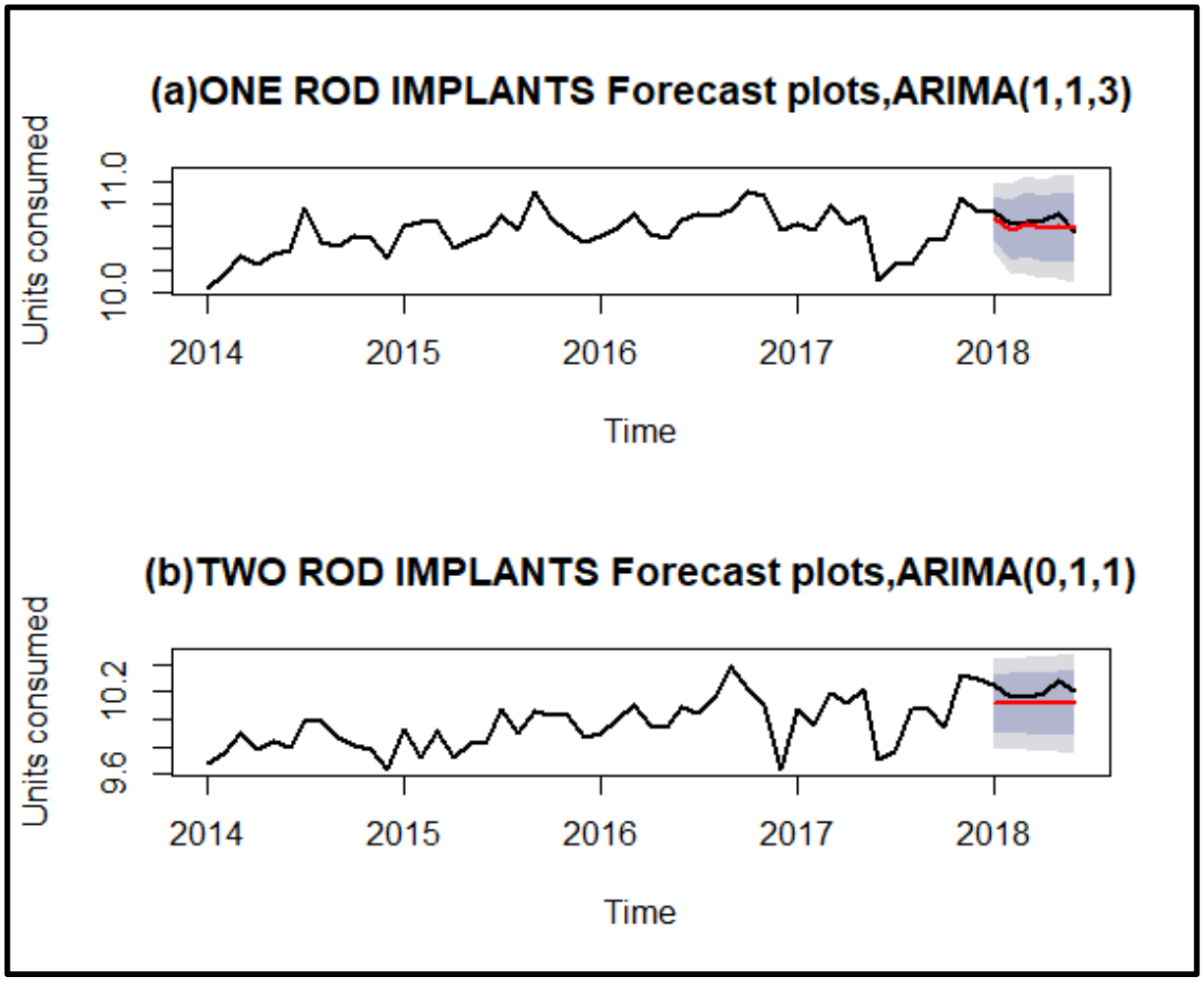



Figure 4-10: Comparison between forecasts and actual data for one and two-rod implants

For intrauterine contraceptive devices (Figure 4-11 a), the predicted mean was within the 95% forecast interval from January to March 2018 compared to the actual consumption 2018 but it was higher than the actual consumption from April to June 2018. For injectables (Figure 4-11 b), the forecasts were consistently higher than the actual consumption.

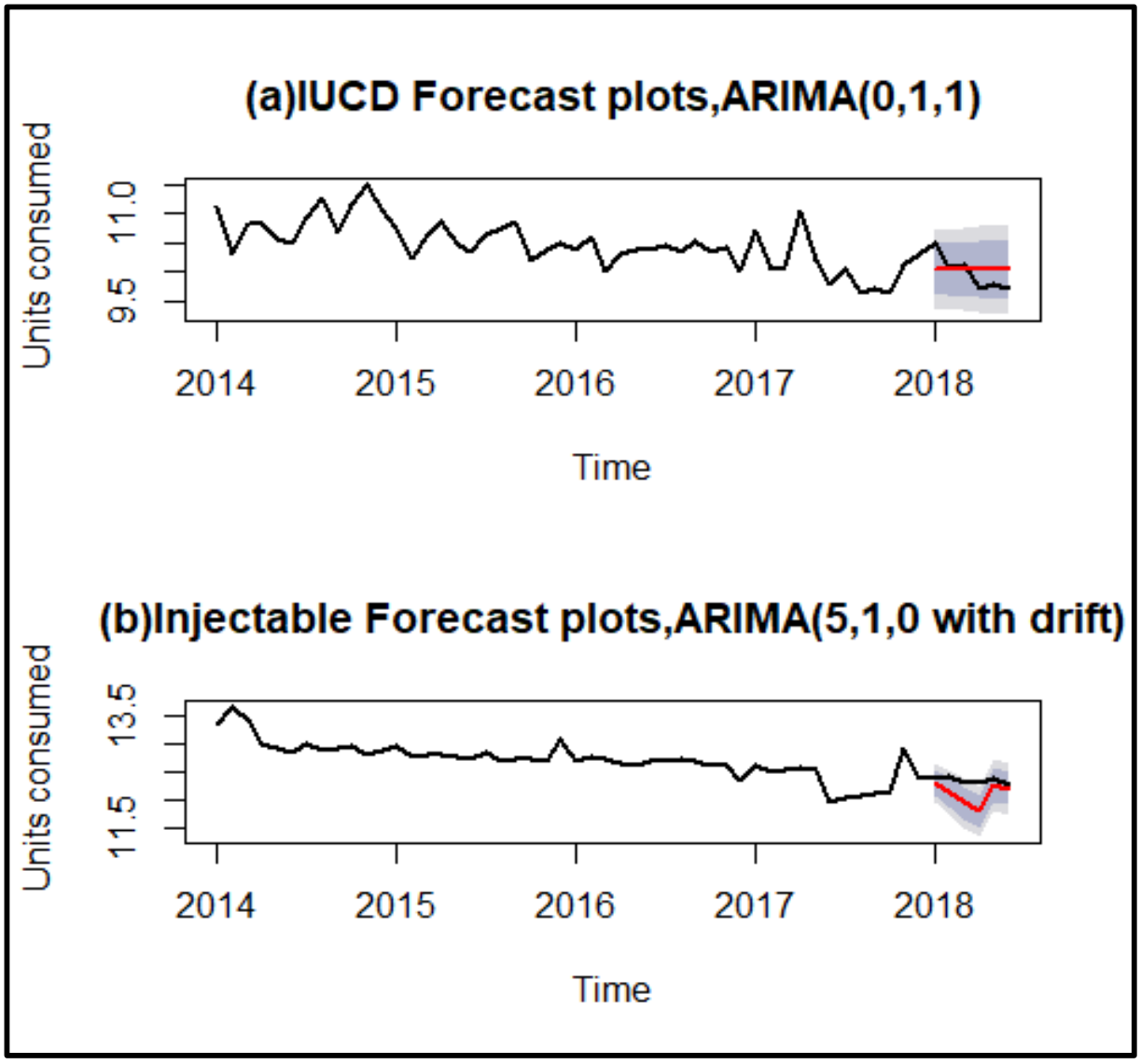



Figure 4-11: Comparison between forecasts and actual data for intrauterine contraceptive devices and injectables.

### 4.5 Exponential smoothing with underlying state space models

To determine the best fit models and their parameters for each contraceptive using the exponential smoothing with underlying state space models, the "ets" function was used and the results are as shown in Table 4-6. The ETS acronym stands for error, trend and seasonality components for a time series respectively.

Table 4-6: Best fit exponential smoothing models for contraceptives

| FP Commodity | Model | AIC | AICc | BIC |
|---|---|---|---|---|
| POP | ETS (M,N,N) | 36.473 | 37.018 | 42.086 |
| COC | ETS (A,N,N) | 34.992 | 35.538 | 40.606 |
| IUCD | ETS (M,N,N | 86.280 | 86.825 | 91.893 |
| Injectables | ETS(A,N,N) | 36.606 | 37.151 | 91.893 |
| One rod implants | ETS(M,N,N) | 23.390 | 23.935 | 29.003 |
| Two rod implants | ETS(A,A,N) | 13.015 | 14.443 | 22.371 |

ETS (M, N, N)- is a model with multiplicative errors, no trend and no seasonality.
ETS (A, N, N) is a model with additive errors, no trend and no seasonality
ETS (A, A, N) is a model with additive errors, additive trend and no seasonality.

### 4.5.1 Model diagnostics for exponential smoothing and underlying state space models.

The residuals for the selected models were examined for autocorrelation and normal distribution using the Ljung Box and the Shapiro Wilk tests respectively as shown in Table 4-7. The fit statistics for the training data set from January 2014 to December 2017 are attached in Appendix I while the out sample forecasts fit statistics (test data) are as presented in Table 4-8.

Table 4-7 Test for normal distribution and auto-correlation of residuals for ETS models

| FP Commodity | ETS Model | Ljung Box Test | Shapiro Wilk Test |
|---|---|---|---|
| | | (P-value) | (P-value) |
| POP | ETS (M,N,N) | 0.720 | 0.483 |
| COC | ETS (A,N,N) | 0.445 | 0.004 |
| IUCD | ETS (M,N,N | 0.854 | 0.923 |
| Injectables | ETS(A,N,N) | 0.975 | 0.000 |
| One rod implants | ETS(M,N,N) | 0.922 | 0.143 |
| Two rod implants | ETS(A,A,N) | 0.168 | 0.065 |

From Table 4-7, the residuals for all contraceptives were not auto-correlated. The residuals for most contraceptives were normally distributed except for injectables and combined oral contraceptives. Lack of normal distribution of residuals was an indication that the model could be improved. The models were acceptable because the residuals were not autocorrelated. Lack of normal distribution of residuals also indicated that the prediction intervals were not normally

distributed. The ACF and PACF of the residuals were plotted and are attached in Appendices N and O. The point forecasts for the selected models are attached in Appendix P.

### 4.5.2 Validation of the exponential smoothing with underlying state space models

Actual consumption of contraceptives from January to June 2018 was used to validate the forecasting models. Comparison between the point forecasts and actual consumption were made. The point forecasts were also overlaid over the actual consumption as shown in Appendix Q

For progestin-only pills (Figure 4-12 a), the predicted mean consumption was consistently higher than the actual consumption in the forecasting period. The actual consumption was within the 95% prediction interval. The forecasts did not reflect a decline in consumption from April to June 2018.

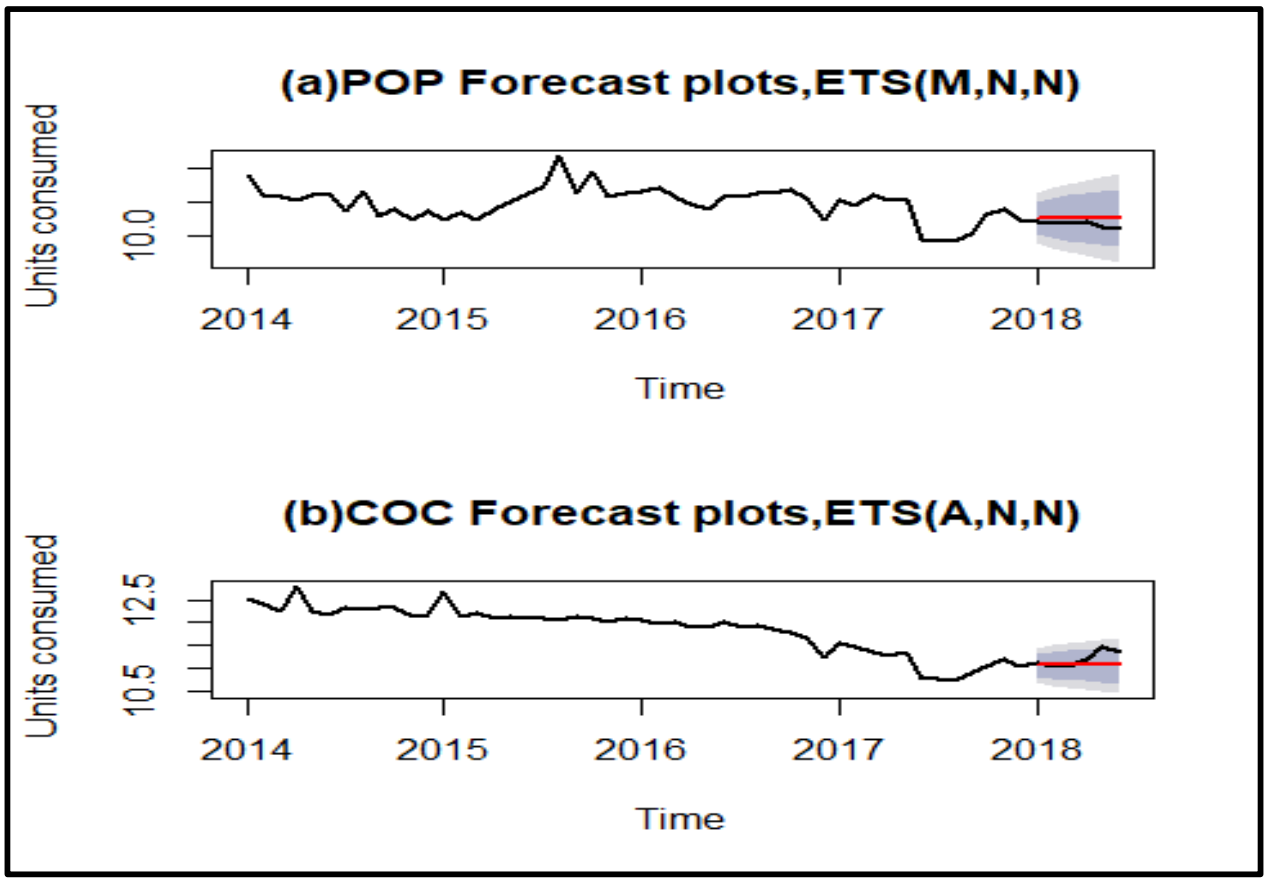



Figure 4-12: Comparison between actual consumption and forecasted consumption for COCs and POPs

For combined oral contraceptives (Figure 4-12 a), the predicted mean consumption was similar to the actual consumption in the January, February, and March and lower from April to June during

the forecasting period. The forecasts did not reflect the increase in consumption of combined oral contraceptives towards May 2018 but it was within the 95% prediction interval.

The predicted mean consumption for Intrauterine devices was higher than actual consumption in January and lower from April to June (Figure 4-13 a). The forecast did not reflect a decline in consumption in April to June and had the highest prediction error.

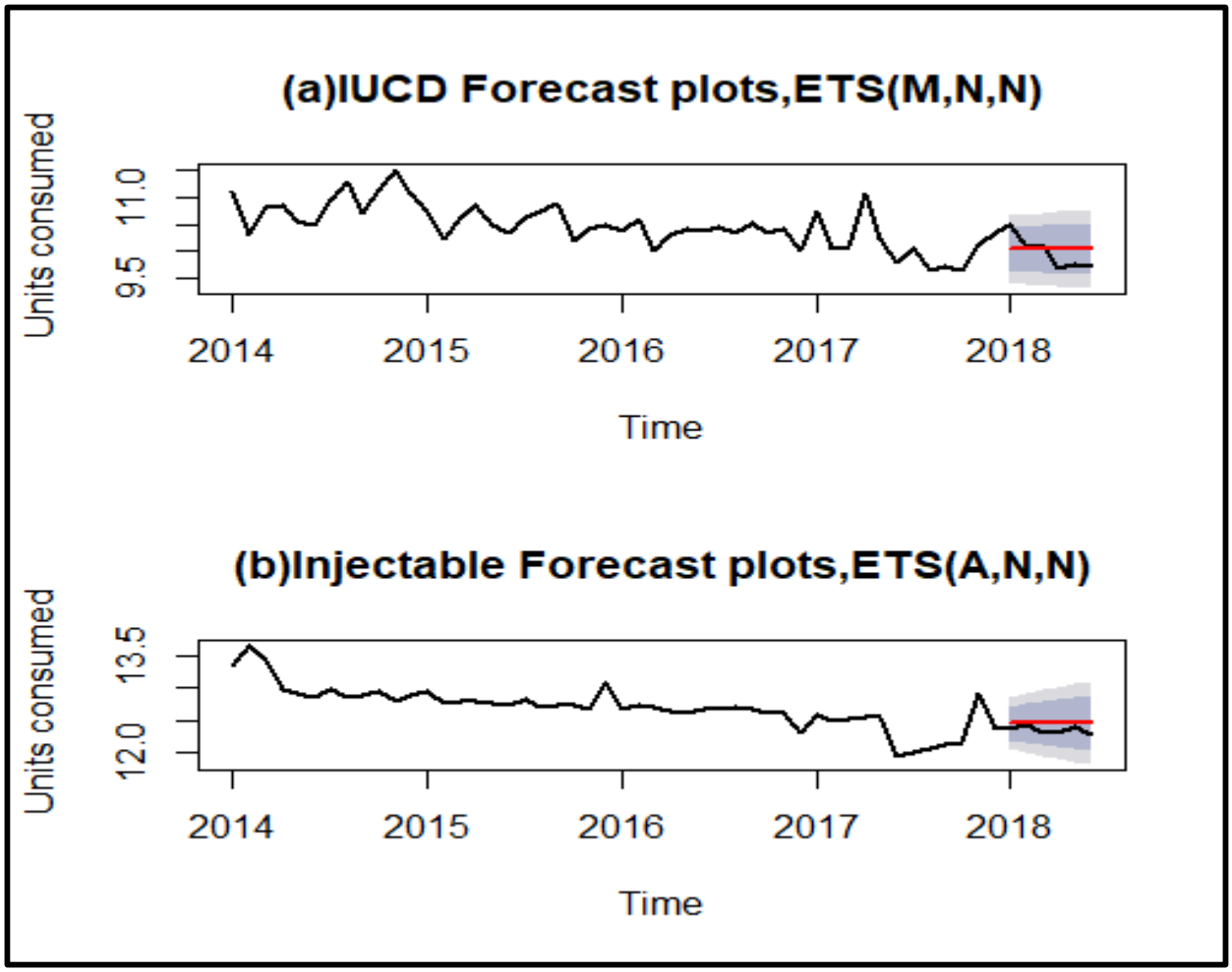



Figure 4-13: Comparison between actual consumption and forecasted consumption for IUCDs and injectables

The mean predicted consumption for injectables (Figure 4-13 b) was only slightly lower than the actual consumption in March, April, and June. The prediction error was low during the forecasting period and within the 95% prediction interval.

The predicted mean of consumption for one-rod implants (Figure 4-14 a) was slightly higher compared to the actual consumption during the forecasting period but within the 80% prediction interval. The mean predicted consumption for two-rod implants (Figure 4-14 b), was slightly lower than actual consumption in January, May, and June. The prediction error was highest in May and the prediction was within the 95% prediction intervals.

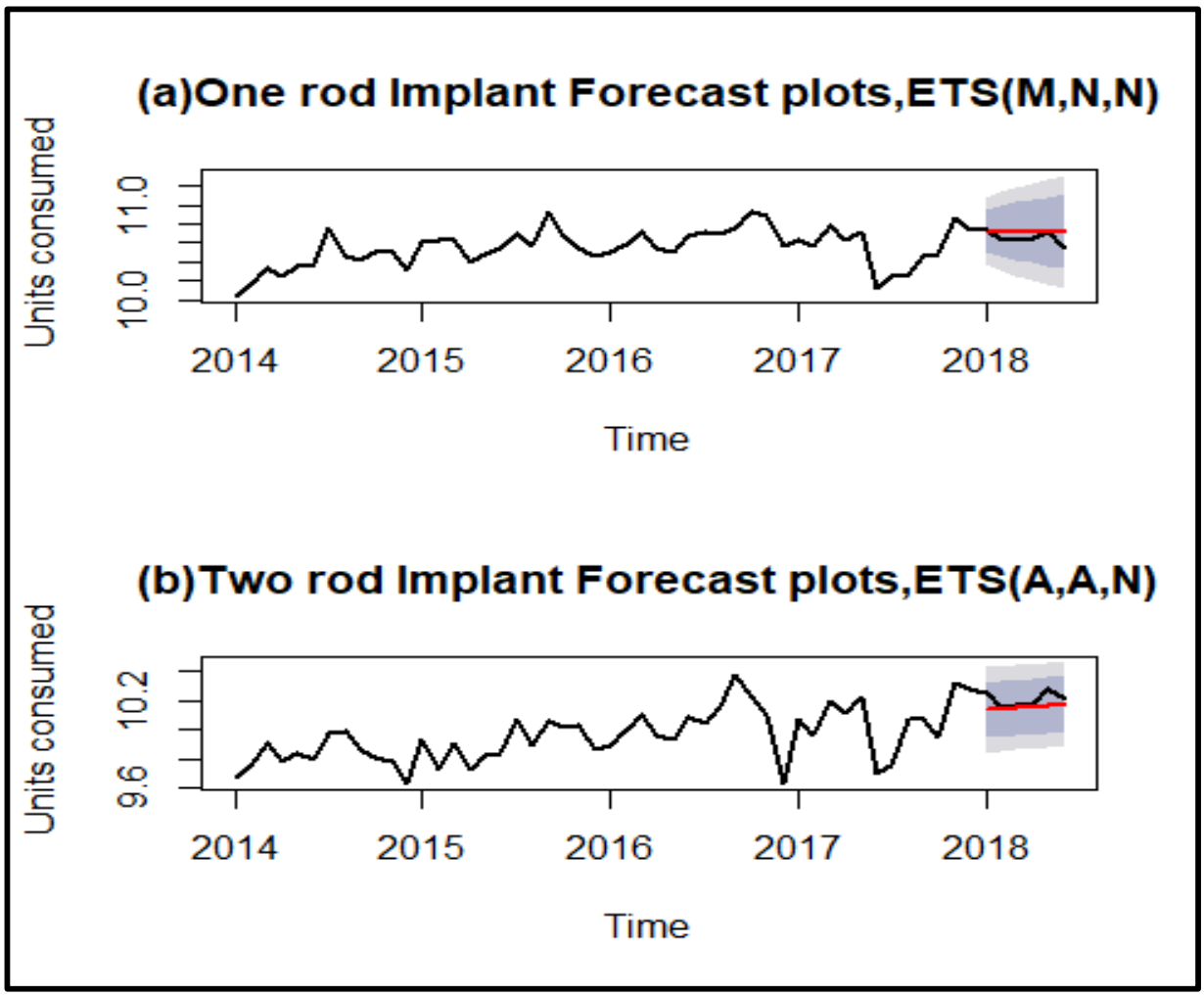



Figure 4-14: Comparison between actual consumption and forecasted consumption for one and two-rod implants

### 4.6 Comparison between ARIMA method and the exponential smoothing with underlying space models.

The forecasts accuracies of the modeling approaches were compared by examining the training and test fit statistics as presented in Appendix 1 and Table 4-8 respectively. The Mean Absolute

Error (MAE), the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE) were used to compare the forecast errors for each of the models. The model with the least training and test fit statistics was chosen to model and forecast the consumption.

Table 4-8: Test data fit characteristics for contraceptives

| | **MODEL** | **ME** | **RMSE** | **MAE** | **MPE** | **MAPE** | **ACF1** | **Theil's U** |
|---|---|---|---|---|---|---|---|---|
| POP | ARIMA(0,1,1) | -0.109 | 0.115 | 0.109 | -1.073 | 1.073 | 0.265 | 3.073 |
| | ETS (M,N,N) | -0.092 | 0.099 | 0.092 | -0.902 | 0.902 | 0.230 | 2.739 |
| COC | ARIMA(1,1,0) with drift | 0.305 | 0.370 | 0.305 | 2.696 | 2.696 | 0.581 | 2.617 |
| | ETS (A,N,N) | 0.136 | 0.212 | 0.157 | 1.191 | 1.387 | 0.536 | 1.511 |
| IUCD | ARIMA(0,1,1) | -0.054 | 0.288 | 0.249 | -0.621 | 2.495 | 0.267 | 0.911 |
| | ETS(M,N,N | -0.054 | 0.288 | 0.249 | -0.625 | 2.495 | 0.267 | 0.912 |
| Injectables | ARIMA(5,1,0) with drift | 0.238 | 0.289 | 0.238 | 1.928 | 1.928 | 0.125 | 3.662 |
| | ETS(A,N,N) | -0.117 | 0.128 | 0.117 | -0.949 | 0.949 | -0.300 | 1.555 |
| One rod Implants | ARIMA(1,1,3) | 0.048 | 0.066 | 0.059 | 0.447 | 0.553 | -0.354 | 0.702 |
| | ETS M,N,N | -0.065 | 0.090 | 0.072 | -0.611 | 0.676 | -0.375 | 1.021 |
| Two-rod Implants | ARIMA(0,1,1) | 0.093 | 0.103 | 0.093 | 0.910 | 0.910 | -0.061 | 1.392 |
| | ETS(A,A,N) | 0.052 | 0.068 | 0.052 | 0.502 | 0.502 | -0.236 | 0.802 |

**Key:** ME-mean Error, RMSE-Root Mean Squared Error, MAE-Mean Absolute Error, MPE-Mean Percentage Error, MAPE- Mean Absolute Percentage Error and ACF-Autocorrelation coefficient

The most optimal model for POPs was the ETS (M, N, N) because it gave the lowest value for Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE). However, this model tended to underestimate consumption because the mean error (-0.092) and mean percentage error (-0.902) were negative.

The most optimal model for consumption of intrauterine contraceptive devices was ETS (M, N, N). However, with regards to the measures of accuracy, the ARIMA model (0,1,1) performed similarly to the ETS model and had similar RMSE and MAE values. Both models also underestimated the consumption because the mean error was -0.054.

For combined oral contraceptives, the ETS (A, N, N) model was the most optimal and performed better than ARIMA (0,1,1) model because the RMSE, MAE, and MPE for the ETS model were about half those of ARIMA model. For the ETS model, the mean error and mean percentage error were positive indicating that the forecasts were overestimates of actual consumption in 2018.

The best model for injectables was ETS (A, N, N) whereby the RMSE, MAE, and MAPE were far less than values for ARIMA (5,0,1) model. The forecasts for injectables were less than the actual values of validation data because the mean error was -0.117. For two rod implants, the optimal model was ETS (A, A, N) and the forecasts were overestimates with a mean error of 0.052.

The only family planning commodity for which the ARIMA model was better than the ETS model was the one-rod implants. The ARIMA (1,1,3) model had a mean error of 0.048 which was the smallest indicating that it gave a very good forecast. The forecasts tended to overestimate the actual consumption in 2018.

# CHAPTER FIVE: DISCUSSION OF RESULTS

## 5.1 Discussion

The study was unique because it analyzed actual consumption of contraceptives, unlike other studies which analyzed trends based on the responses from the national demographic health surveys.

The use of combined oral contraceptives, injectables, and intrauterine contraceptives steadily declined while that of implants increased from 2014 to 2017 as shown in Figure 4-1. The use of progestin-only pills increased up to 2015 then declined in 2016 and 2017. The decline could be attributed to a shift towards the use of long-term reversible methods especially implants. There were advocacy programs run by various partners prior to the review period. The Kenya Urban Reproductive Health Initiative (Tupange program), an initiative by the government and various partners ended in 2014 and resulted in the rise of the use of long-term methods especially implants in 2014 and a reduction in the use of injectables and pills as compared to the baseline (2010). The Tupange program targeted the urban poor areas in Nairobi, Kakamega, Mombasa, Kisumu and Machakos counties for women of 15 to 49 years of age so as to increase use modern contraceptives (37–40).

The rise in the use of implants could also be associated to the launch of the Implant Access Program in 2013 where a group of private and public organizations collaborated with manufacturers, Bayer and Merck, to ensure access to implants such as Jadelle®, Implanon® and Implanon NXT® to poor countries through reduced prices of up to 50%. The Family Planning 2020 (FP 2020) countries of which Kenya belongs is a beneficiary. The program is also involved training of health workers on insertion and removal of implants (41). Kenya was one of the countries with the highest procurement of implants in 2015 (42). As part of the Implant Access program, the best practice training and implementation were conducted in Kilifi and Migori counties (42).

The proportion of women seeking family planning services declined from 29.7 to 18.5% over the four years as shown in Table 4-2. This was consistent with the Performance, Monitoring, and Accountability Survey (PMA 2020), which was done in 2016 (round five) by the Ministry of Health, Kenya in collaboration with various partners in eleven counties. The survey showed a reduction in the modern methods contraceptive prevalence rate from 46.0 in 2015 to 44.2% in 2016 (43).

There were notable peaks in the consumption of various FP commodities. There were peaks in consumption of Combined Oral Contraceptives (COC's) in April 2014 and January 2015 as presented in Figure 4-2 (a). During this period only 5.3 and 8.7% of the facilities providing family planning services had stock-outs of COC's respectively (8). The number of facilities providing FP services with stock-outs of COC 's increased from 5.3% in January 2014 to 34.7% in December 2017 (8). There was a general decline in the consumption of COC's from 2014 to 2017 due to a shift to long and permanent methods.

The peak consumption periods for progestin-only pills occurred from August to October 2015 as shown in Figure 4-2 (c). Prior to this period, about 38.5% of health facilities had stock-outs of POP while the number of facilities experiencing stock-outs had reduced to an average of 28.2% in this period (8). The erratic pattern in consumption of POP's could be explained by frequent stock-outs and erratic supply of the commodities. The spikes in consumption could also be as a result of the global postpartum family planning movement following a meeting titled "Accelerating Access to Postpartum Family Planning in Sub Saharan Africa and Asia" that was held in June 2015. Kenya was one of the focus countries in improving access to family planning to postpartum women (41,44).

There was a high consumption of IUCDs (Figure 4-3 (a)) in mid to end of 2014 and this could be attributed to outreach activities carried out by partners and health facilities. During this period an average of 20% of health facilities providing FP services had stock-outs (8). The percentage of women in Kenya using IUCDs was relatively low at 3.4 % in 2014 (5). A study done in two Nairobi public hospitals showed that myths and misconceptions about IUCDs were the main barriers to their uptake (45).

In Kenya, injectables are very popular and 26.4% of women of reproductive age were using them in 2014 (5). The highest proportion of women who sought FP services from 2014 to 2017 used injectables and the proportion was above 60% in the review period. However, the use of injectables had a declining trend from 2014 to 2017 despite the number of facilities having stock outs being below 7.7% in the review period (8). This could be attributed to the shift to long-term contraceptive methods. The high peaks at the end of 2016 and 2017 were due to the resumption of nurses to work after the industrial strike in December 2016 and November 2017 respectively (46,47).

There were high peaks in consumption for one-rod implants in September 2015 and October 2016. This could be attributed to low stock out levels in the country. Only 10.4 and 9.3% of health facilities providing FP services had stock-outs of one-rod implants and this could also be attributed to outreaches organized by health facilities and partners (8). An easier to insert and remove one-rod implant( Implanon NXT®) was piloted in Kenya in 2015 and rolled out in the country in 2016 (41,48).

Two-rod implants also had high periods of consumption in September 2016 and November 2017. This could be attributed to the outreach activities by health facilities and partners and resumption of FP services after the nurses strike respectively (47). There was also a low consumption of two-rod implants in December 2014 and this could be attributed to having 26.1% of facilities providing FP services having stock outs (8). The December 2016 nurses strike could also explain the low consumption of two-rod implants in the country since a number of facilities having stock outs had reduced from 17.2% in November 2016 to 14.5% in December 2015 (46).

There was a general decline in the number of all contraceptives consumed in July and August 2017 as shown in Figures 4-2 and 4-3. This could be attributed to the national wide nurse's strike that affected the public sector health facilities service delivery (47). The Kenya public sector experienced several industrial strikes by health workers since devolution in 2013. The nurse's strike had a major impact on the provision of family planning services in the health facilities as they are the primary service providers. There were several strikes by nurses in the country and various counties during the period of evaluation. In 2014 and 2015, several counties experienced industrial disputes by nurses such as Nandi, Mombasa, Homabay, Kilifi, Kericho, Vihiga, Siaya and Kakamega (49). There were also a national wide two weeks' nurses strike in December 2016 and a concurrent strike by doctors which lasted three months. Pharmacists are tasked with reporting and ordering of contraceptives at the sub-county and county levels (46). In 2017, there was a five month's strike by nurses which began in June 2017 and ended in November 2017.This paralyzed health care delivery in public health facilities (47). A study that was done in 2015 to review the effect of industrial actions by nurses at Rift Valley Provincial General Hospital- Nakuru showed that strikes greatly affected service delivery in the hospital. Strikes led to shutting down of hospitals and turning away of clients at the hospital (50).

Exploratory analysis of the data sets showed that there were apparent periods of high and low consumption within each year. Each family planning commodity had different months of high consumption. The consumption of COCs was highest in January; POPs in August; one-rod implants in July; two-rod implants in September; injectables in December; and IUCDs in November. Most FP commodities had the lowest consumption in December except for IUCDs and injectables whose lowest consumption was in June. The low uptake in December could possibly be explained by the long holidays which are associated with merrymaking hence the low uptake of any intervention.

Correlation between consumption data and service data for injectables, intrauterine contraceptive devices and implants in Figures 4-6 and 4-7 revealed discrepancies in the quantities reported. The service and consumption data for injectables and intrauterine contraceptives had a strong correlation coefficient while implants had a low negative correlation coefficient. The difference could be partially accounted for by the losses and expiries but they were minimal. This could also be attributed to errors in reporting the service data or consumption data. Ideally, the consumption data and service data should be the same for contraceptives issued per piece or unit which is the case for injectables, implants and intrauterine contraceptives devices after accounting for losses. This showed that there was a gap in the reporting of contraceptives in the facilities hence need for capacity building to bridge the gap.

The time series analysis was done to forecast consumption of the FP commodities for six months using both the ARIMA model and exponential smoothing. The exponential smoothing (ETS) model was the best suited for forecasting consumption of injectables, combined oral contraceptives, intrauterine contraceptive devices, progestin-only pills, and two-rod implants. The ARIMA models were suitable for forecasting one-rod implants. The two-rod implant was best modeled by the ETS model. The models chosen had the lowest mean absolute percentage error, root means squared error and mean absolute scale error for all the commodities evaluated for the six months forecasting interval (51).

The Performance, Monitoring, and Accountability (PMA) 2020 survey in 2016 showed similar trends in the consumption of FP commodities (43). There was an increase in the consumption of implants from 23.4 to 25.5% and then to 30.2% from round three, four and five respectively among married women. The injectables reduced from 50.1 to 46.2% then to 46.0% over the same period.

The pills (combined oral contraceptives and progestin-only pills) use among married women also reduced from 12.3 to 11.9% then to 8.5 % from round three, four to five respectively (43).

# CHAPTER SIX: CONCLUSION AND RECOMMENDATIONS

## 6.1 Conclusion

There was a general shift in the use of modern contraceptives from short term to long term acting reversible methods. This was shown by the decline in the use of pills, injectables and intrauterine contraceptive devices and the increase in the use of implants. Each of the family planning commodity had a unique seasonal pattern and most of the commodities had the lowest consumption in December. The consumption was greatly affected by the availability of methods and services at the providing facilities. It is therefore important to ensure constant and timely supply of contraceptives in the facilities. There was a significant difference between the reported consumption data and service point data for injectables, implants and more so the intrauterine contraceptive devices. The ETS model was the most suitable for forecasting consumption of contraceptives.

## 6.2 Recommendations for policy and practice

There is a need for the agencies responsible for procurement to take into consideration the shift in the use of contraceptives during the forecasting and procurement process. It is also important to ensure continuous availability of health workers and the commodities in the providing facilities to ensure regular uptake of contraceptives so as to increase the contraceptive prevalence rate.

There is also a need for capacity building among health workers on documentation and reporting on the use of contraceptives to bridge the gap between reported service point data and consumption data.

## 6.3 Recommendations for research

Further studies are required to verify the major reasons why there are discrepancies in the reported consumption and service point data at the facility level. There also need to determine why the use of intrauterine contraceptive devices is still low despite it being a long-term method and ways to improve its uptake. The number of girls maturing into the age bracket 15-49 years of age and those attaining 50 years and beyond should also be considered while determining future consumption of contraceptives.

## REFERENCES


1. WHO. Family Planning Contraception [Internet]. Facts Sheet. World Health Organization; 2016 [cited 2017 Jun 2]. Available from: http://who.int/mediacentre/factsheets/fs351/en/
2. Government of Kenya. The Constitution of Kenya, 2010 [Internet]. Kenya; 2010 p. 30. Available from: www.kenyalaw.org
3. Government of Kenya. Reproductive Health Care Bill, 2014 [Internet]. 2014 p. 290. Available from: http://kenyalaw.org/kl/fileadmin/pdfdownloads/bills/2014/ReproductiveHealthCareBill2014__1_.pdf
4. Health M of. Republic of Kenya: Family Planning Commodities Quantification and Supply Planning Review 2016-2018 Technical Report. 2018.
5. Kenya National Bureau of Statistics. Kenya 2014 Demographic and Health Survey [Internet]. 2014 [cited 2017 May 17]. Available from: https://dhsprogram.com/pubs/pdf/fr308/fr308.pdf
6. United Nations. Trends in Contraceptive Use Worldwide 2015 [Internet]. 2015 [cited 2017 Jun 21]. Available from: http://www.un.org/en/development/desa/population/publications/pdf/family/trendsContraceptiveUse2015Report.pdf
7. Douglas-Durham E, Blanchard K, Higgins S. Contraceptive Stockouts: A review of the published and grey literature [Internet]. Reproductive Health Supplies Coalition. 2015 [cited 2017 May 17]. Available from: https://noemptyshelves.org/wp-content/uploads/2015/09/Contraceptive_Stockouts_Lit_review.pdf
8. Ministry of Health Kenya. Reproductive and Maternal Health Services Unit [Internet]. 2018 [cited 2018 Jul 3]. Available from: https://familyplanning.nascop.org/home/national-method-mix
9. Sedgh G, Hussain R. Reasons for Contraceptive Nonuse among Women Having Unmet Need for Contraception in Developing Countries. Stud Fam Plann [Internet]. 2014 [cited 2017 Jun 23];45((2)):151–69. Available from: https://www.guttmacher.org/sites/default/files/pdfs/pubs/journals/j.1728-

4465.2014.00382.x.pdf

10. Adetunji JA. Rising popularity of injectable contraceptives in sub-Saharan Africa. African Popul Stud. 2011;25(2):587–604.

11. Bertrand JT, Sullivan TM, Knowles EA, Zeeshan MF, Shelton JD. Contraceptive method skew and shifts in method mix in low- and middle-income countries. Int Perspect Sex Reprod Health. 2014;40(3):144–53.

12. Management Sciences for Health/ Health Commodities and Services Management Program Kenya. Family Planning Commodity Quantification and Supply Planning Review FY2013/14-2014/15. 2014.

13. Seiber EE, Bertrand JT, Sullivan TM. Changes in contraceptive method mix in developing countries. Int Fam Plan Perspect. 2007;33(3):117–23.

14. Gakii N. Assessment of Hormonal Contraceptive Use Among Women at Kenyatta National Hospital. University of Nairobi; 2014.

15. World Health Organization. Hormonal Contraceptives, Progestogens Only. Int Agency Res Cancer Monogr [Internet]. 1999 [cited 2017 Jun 20];72:339–85. Available from: https://monographs.iarc.fr/ENG/Monographs/vol72/mono72-7.pdf

16. Ministry of Public Health and Sanitation. National Family Planning Guidelines for Service Providers [Internet]. Fourth. Nairobi: Division of Reproductive Health; 2010 [cited 2017 Jun 21]. Available from: https://www.k4health.org/sites/default/files/Kenya FP Guidelines 2010 final signed_full text.pdf

17. World Health Organization Department of Reproductive Health and Research (WHO/RHR) and Johns Hopkins Bloomberg School of Public Health/Center for Communication Programs (CCP) K for HP. Family Planning: A Global Handbook for Providers (2011 update). Fam Heal Int. 2011;109–30.

18. Jalang'o R. Determinants of Contraceptive Use Among Breast Feeding Women in Kisii Level 5 Hospital. University of Nairobi; 2015.

19. Agha S, Do M. The quality of family planning services and client satisfaction in the public and private sectors in Kenya. Int J Qual Heal Care. 2009;21(2):87–96.

20. Anguko A. Determinants of Contraceptive Use Among Women of Reproductive Age in North Eastern Kenya. University of Nairobi; 2014.

21. Kipyegon NL, of Nairobi U. Factors Influencing Use of Modern Contraceptives Among Kenyan-Somali Women Aged Between 15-49 Years A Matched Control-case Study of Korogocho and Kiamaiko. 7441 [cited 2017 Jul 17]; Available from: http://erepository.uonbi.ac.ke/bitstream/handle/11295/99618/Lang‟at_Factors Influencing Use of Modern Contraceptives Among Kenyan-Somali Women Aged Between 15-49 Years A Matched Control-case Study of Korogocho and Kiamaiko.pdf?sequence=1&isAllowed=y

22. Guure C, Maya ET, Dery S, Vrom B, Alotaibi RM, Rezk HR, et al. Factors influencing unmet need for family planning among Ghanaian married / union women : a multinomial mixed-effects logistic regression modeling approach. 2019;1–12.

23. United Nations. Transforming Our World: The 2030 Agenda for Sustainable Development [Internet]. United Nations Development Programme. 2017 [cited 2017 Jun 2]. Available from: http://www.undp.org/content/undp/en/home/sustainable-development-goals/goal-3-good-health-and-well-being/targets/

24. Ngure P. A Review of National and District Policies and Budgets Family Planning in Kenya [Internet]. 2014 [cited 2017 May 17]. Available from: https://www.dsw.org/uploads/tx_aedswpublication/family-planning-kenya_update.pdf

25. Ministry of Health. National and County Health Budget Analysis fy 2016/17 [Internet]. 2016. Available from: https://www.google.com/search?q=National+and+County+Health+Budget+Analysis+fy+2016%2F17&oq=National+and+County+Health+Budget+Analysis+fy+2016%2F17&sourceid=chrome&ie=UTF-8

26. United States Agency for International Development. Accelerating Access to Postpartum Family Planning (PPFP) in Sub-Saharan Africa and Asia PPFP Country Programming Strategies Worksheet [Internet]. 2013 [cited 2017 May 17]. Available from: http://ec2-54-210-230-186.compute-1.amazonaws.com/wp-content/uploads/2015/10/Kenya-PPFP-Country-Programming-Strategies-Worksheet_Near-Final_Kenya.pdf

27. National Council for Population and Development/Ministry of Health. 2015 Kenya Health Facility Assessment: An Assessment of Availability of Family Planning and Maternal/Reproductive Health Commodities/Medicines and Services [Internet]. 2016. Available from: https://www.afidep.org/?p=6034

28. Ministry of Health. Kenya Reproductive, Maternal, Newborn, Child and Adolescent Health (RMNCAH) Investment Framework [Internet]. 2016 [cited 2017 May 17]. Available from: http://ec2-54-210-230-186.compute-1.amazonaws.com/wp-content/uploads/2016/10/Kenya-Reproductive-Maternal-Newborn-Child-and-Adolescent-Health-RMNCAH-Investment-Framework-2016.pdf

29. Ministry of Health. Republic of Kenya Reproductive Health Commodity Security Strategy 2013-2017. 2013.

30. World Health Organization. Estimating Drug Requirements - A Practical Manual: Part I: Introduction: Module 1: Objectives and use of the manual: 2. The Two Methods of quantification. [Internet]. 1995 [cited 2017 Oct 5]. Available from: http://apps.who.int/medicinedocs/en/d/Jh2931e/2.1.2.html

31. Ministry of Health. Republic of Kenya Family Planning Commodities Quantification and Supply Plan Technical Report. 2016.

32. Hong, R., Fronczak, N., Chinbuah, A., & Miller R. Ghana Trend Analysis for Family Planning Services 1993,1996,2002. Demographic Trend Reports No.1. 2005.

33. Shiferaw S, Abdullah M, Mekonnen Y, Maïga A, Akinyemi A, Amouzou A. Trends in contraceptive use and distribution of births with demographic risk factors in Ethiopia: A sub-national analysis. Glob Health Action. 2015;8(1):1–10.

34. Hounton S, Barros AJDD, Amouzou A, Shiferaw S, Maïga A, Akinyemi A, et al. Patterns and trends of contraceptive use among sexually active adolescents in Burkina Faso, Ethiopia, and Nigeria: Evidence from cross-sectional studies. Glob Health Action [Internet]. 2015 [cited 2017 Oct 4];8(1):1–11. Available from: http://www.ncbi.nlm.nih.gov/pubmed/26562143

35. Avril Coghlan. A Little Book of R for Time Series [Internet]. Release 2. 2017. 12–66 p. Available from: http://cdn.bitbucket.org/psylab/r-books/downloads/Coghlan2014.pdf

36. Rob H, Yeasmin K. Automatic Time Series Forecasting : The forecast Package for R Automatic time series forecasting : the forecast package for R. J Stat Softw. 2014;(July 2008).

37. Kenya Urban Reproductive Health Initiative. Kenya The Kenya Urban Reproductive Health Initiative ( Tupange ) Endline Findings for Machakos. 2014.

38. Kenya Urban Reproductive Health Initiative. Kenya The Kenya Urban Reproductive Health Initiative ( Tupange ) Endline Findings for Mombasa. 2015.

39. Kenya Urban Reproductive Health Initiative. Kenya The Kenya Urban Reproductive Health Initiative ( Tupange ) Endline Findings for Kisumu. 2014.

40. Kenya Urban Reproductive Health Initiative. Kenya The Kenya Urban Reproductive Health Initiative ( Tupange ) Endline Findings for Kakamega. 2014.

41. United Nation Foundation. Family Planning 2020 [Internet]. 2018 [cited 2018 Jul 3]. Available from: http://www.familyplanning2020.org/entities/77/commitments

42. Sergison JE, Stalter RM, Callahan RL, Rademacher KH, Steiner MJ. Cost of Contraceptive Implant Removal Services Must Be Considered When Responding to the Growing Demand for Removals. Glob Heal Sci Pract [Internet]. 2017 [cited 2018 Jul 3];5(2):330–2. Available from: http://www.ncbi.nlm.nih.gov/pubmed/28655806

43. Ministry of Health Kenya. PMA2016/KENYA-R5 Indicators for Access, Equity, Quality and Choice Sample Design [Internet]. 2017 [cited 2018 Jul 3]. Available from: https://www.gatesinstitute.org/sites/default/files/KER5-2PG-FP-Indicator-Brief-v13-2017-07.14.sed_.pdf

44. Remarks W, Kerrigan M, Lessons P, Muthigani W. Accelerating access to post parturm family planning- Country action follow -up Webinar. In 2015.

45. Florence Mbuthia. Intrauterine Device Uptake Among Women Seeking Family Planning Services At Mbagathi And Mama Lucy Kibaki Hospitals In Nairobi County, Kenya [Internet]. 2014 [cited 2018 Jul 4]. Available from: http://ir-library.ku.ac.ke/bitstream/handle/123456789/13346/Intrauterine device uptake among women seeking family.pdf;sequence=1

46. Daily Nation. Nurses union calls off strike - Daily Nation. 2016 [cited 2018 Mar 27];

Available from: https://www.nation.co.ke/news/Nurses-union-calls-off-strike-sign-pact-with-governors/1056-3486346-hr59m8/index.html

47. Daily Nation. Nurses end their 5-month strike - Daily Nation. 2017 [cited 2018 Mar 27]; Available from: https://www.nation.co.ke/news/Kenyan-nurses-end-4-month-strike-after-deal-with-State/1056-4166940-mo35skz/index.html

48. MSD. Access to Reproductive Health – MSD Responsibility [Internet]. 2018 [cited 2018 Jul 6]. Available from: https://www.msdresponsibility.com/access-to-health/womens-health/access-to-reproductive-health/

49. Daily Nation. Suffering as nurses strike hits counties - Daily Nation. 2015 [cited 2018 Mar 27]; Available from: https://www.nation.co.ke/news/Suffering-as-nurses-strike-hits-counties/1056-2838288-wc9ifwz/index.html

50. Shitsinzi RS. Influence of industrial action on provision of medical services by nurses in public hospitals: a case of rift valley provincial general hospital, Nakuru county, Kenya. 2015 [cited 2018 Mar 27]; Available from: http://erepository.uonbi.ac.ke/handle/11295/90540

51. Hyndman R, Athanasopoulos G. Forecasting: Principles and Practice. In: Forecasting: Principles and Practice [Internet]. 2018 [cited 2018 Aug 27]. Available from: https://otexts.org/fpp2/arima-ets.html

## APPENDICES

### Appendix A: Scripts used for analysis of contraceptives

**Loading data from Excel into R**

```
contraceptives<-read.csv("C:/Users/PERP-PC/Desktop/Thesis proposal/PERPETUADATA/contraceptives.csv", header=TRUE)

coctimeseries<-ts(contraceptives$coc, frequency=12, start=2014)

poptimeseries<-ts(contraceptives$pop, frequency=12, start=2014)

implants1timeseries<-ts(contraceptives$implants1, frequency=12, start=2014)

implants2timeseries<-ts(contraceptives$implants2, frequency=12, start=2014)

iucdtimeseries<-ts(contraceptives$iucd, frequency=12, start=2014)

injectabletimeseries<-ts(contraceptives$injectable, frequency=12, start=2014)

implantstimeseries<-ts(contraceptives$implanttotal, frequency=12, start=2014)
```

**loading service point data**

```
servicepointdata<-read.csv("C:/Users/PERP-PC/Desktop/Thesis proposal/PERPETUADATA/servicepointdata.csv", header=TRUE)

cocsptimeseries<-ts(servicepointdata$coc, frequency=12, start=2014)

popsptimeseries<-ts(servicepointdata$pop, frequency=12, start=2014)

implantsptimeseries<-ts(servicepointdata$implant, frequency=12, start=2014)

iucdsptimeseries<-ts(servicepointdata$iucd, frequency=12, start=2014)

injectablesptimeseries<-ts(servicepointdata$injections, frequency=12, start=2014)
```

**plotting time series data vs service point data**

```
par(mfrow=c(3,2)) # multifigure setup: 3 rows, 2 cols

plot.ts(coctimeseries, ylab="Units consumed", main="(a)COCs consumption")

abline(reg=lm(cocseries~time(cocseries)))

plot.ts(cocsptimeseries, ylab="clients served", main="(b)COC service point data")

abline(reg=lm(cocsptimeseries~time(cocsptimeseries)))

plot.ts(poptimeseries,  ylab="Units consumed", main="(c)POP  consumption")

abline(reg=lm(popseries~time(popseries)))

plot.ts(popsptimeseries, ylab="clients served", main="(d)POP service point data")

abline(reg=lm(popsptimeseries~time(popsptimeseries)))
```

```
plot.ts(injectabletimeseries, ylab="Units consumed", main="(e)Injectables consumption")
abline(reg=lm(injectableseries~time(injectableseries)))
plot.ts(injectablesptimeseries, ylab="clients served", main="(f)Injectable service point data")
abline(reg=lm(injectablesptimeseries~time(injectablesptimeseries)))
par(mfrow=c(3,2))
plot.ts(iucdtimeseries, ylab="Units consumed", main="(a)IUCDs consumption")
abline(reg=lm(iucdtimeseries~time(iucdtimeseries)))
plot.ts(iucdsptimeseries, ylab="clients served", main="(b)IUCDs service point data")
abline(reg=lm(iucdsptimeseries~time(iucdsptimeseries)))
plot.ts(implantstimeseries, ylab="Units consumed", main="(c)Implants consumption")
abline(reg=lm(implantstimeseries~time(implantstimeseries)))
plot.ts(implantsptimeseries, ylab="clients served", main="(d)Implants service point data")
abline(reg=lm(implantsptimeseries~time(implantsptimeseries)))
```

**Decomposing of data**

```
coccomponent<-decompose(coctimeseries)
popcomponent<-decompose(poptimeseries)
implants1component<-decompose(implants1timeseries)
implants2component<-decompose(implants2timeseries)
iucdcomponent<-decompose(iucdtimeseries)
injectablecomponent<-decompose(injectabletimeseries)
```

**Plotting the trend component**

```
par (mfrow=c(3,2))
plot(coccomponent$trend, main="(a)Combined Oral Contraceptives Trend")
plot(popcomponent$trend, main="(b)Progestin Only Pills Trend")
plot(implants1component$trend, main="(c)One Rod Implant Trend")
plot(implants2component$trend, main="(d)Two Rod Implant Trend")
plot(iucdcomponent$trend, main="(e)IUCD Trend")
plot(injectablecomponent$trend, main="(f)Injectables Trend")
```

**Plotting the seasonal component**

```
par (mfrow=c(3,2))
plot(coccomponent$seasonal, main="(a)  Oral Contraceptives Seasonality")
plot(popcomponent$seasonal, main="(b) Progestin Only Pills Season seasonality")
plot(implants1component$seasonal, main="(c) One Rod Implant Trend seasonality")
plot(implants2component$seasonal ,main="(d)Two Rod Implant seasonality")
plot(iucdcomponent$seasonal,main="(e) IUCD seasonality")
plot(injectablecomponent$seasonal ,main="(f) Injectables seasonality")
```

**Determining the seasonal components**

```
coccomponent$seasonal
popcomponent$seasonal
implants1component$seasonal
implants2component$seasonal
iucdcomponent$seasonal
injectablecomponent$seasonal
```

**Generating log transformed series**

```
logcoc<-log(coctimeseries)
logpop<-log (poptimeseries)
logimplant1<-log (implants1timeseries)
logimplant2<-log (implants2timeseries)
logiucd<-log (iucdtimeseries)
loginjectable<-log (injectabletimeseries)
```

**Plotting the log transformed series**

```
plot.ts(logcoc, main="(a)Log COC", ylab="log(Units)")
plot.ts(logpop, main="(b)Log POP",  ylab="log(Units)")
plot.ts(logimplant1, main="(c)Log IMPLANT-1", ylab="log(Units)")
plot.ts(logimplant2, main=" (d)Log IMPLANT-2", ylab="log(Units)")
plot.ts(loginjectable, main="(e)log INJECTABLE", ylab="log(Units)")
plot.ts(logiucd, main="(f)Log IUCD", ylab="log(Units)")
```

**Decomposition of the time series (logged data)**

```
logcoccomponent<-decompose(logcoc)
logpopcomponent<-decompose(logpop)
logimplants1component<-decompose(logimplant1)
logimplants2component<-decompose(logimplant2)
logiucdcomponent<-decompose(logiucd)
loginjectablecomponent<-decompose(loginjectable)
```

**Plotting the trend graphs from the decomposed series**

```
logcoccomponent<-decompose(logcoc)
logpopcomponent<-decompose(logpop)
logimplants1component<-decompose(logimplant1)
logimplants2component<-decompose(logimplant2)
logiucdcomponent<-decompose(logiucd)
loginjectablecomponent<-decompose(loginjectable)
```

**Plotting the trend graphs from the decomposed series**

```
plot(logcoccomponent$trend,  main="Trend of Log COC")
plot(logpopcomponent$trend,   main="Trend of Log POP")
plot(logimplants1component$trend,   main="Trend of Log  IMPLANT-1")
plot(logimplants2component$trend,   main="Trend of Log IMPLANT-2")
plot(logiucdcomponent$trend,   main="Trend of Log IUCD")
plot(loginjectablecomponent$trend,   main="Trend of Log INJECTABLE")
```

**plotting of logged seasonal components**

```
par (mfrow=c(3,2))
plot(logcoccomponent$seasonal)
plot(logpopcomponent$seasonal)
plot(logimplants1component$seasonal)
plot(logimplants2component$seasonal)
plot(logiucdcomponent$seasonal)
plot(loginjectablecomponent$seasonal)
```

**plotting differenced graphs**

```
par (mfrow=c(3,2))
cocseriesdiff1 <- diff(coctimeseries, differences=1)
plot.ts(cocseriesdiff1) # seems adequate
popseriesdiff1 <- diff(poptimeseries, differences=1)
plot.ts(popseriesdiff1) # seems adequate
implants1seriesdiff1 <- diff(implants1timeseries, differences=1)
plot.ts(implants1seriesdiff1) #  there is a clear increasing trend
implants2seriesdiff1 <- diff(implants2timeseries, differences=1)
plot.ts(implants2seriesdiff1) #  there is a clear increasing trend
iucdseriesdiff1 <- diff(iucdtimeseries, differences=1)
plot.ts(iucdseriesdiff1) #
injectableseriesdiff1 <- diff(injectablestimeseries, differences=1)
plot.ts(injectableseriesdiff1) #
```

**Complete transformation**

```
logcoc<-log(coctimeseries)
logpop<-log (poptimeseries)
logimplant1<-log (implants1timeseries)
logimplant2<-log (implants2timeseries)
logiucd<-log (iucdtimeseries)
loginjectable<-log (injectabletimeseries)
```

**Differencing logged data**

```
logpopdiff1 <- diff(logpop, differences=1)
logcocdiff1 <- diff(logcoc, differences=1)
logimplant1diff1 <- diff(logimplant1, differences=1)
logimplant2diff1 <- diff(logimplant2, differences=1)
logiucddiff1 <- diff(logiucd, differences=1)
loginjectablediff1 <- diff(loginjectable, differences=1)
```

**plots of differenced data**

```
par(mfrow=c(3,2))
plot.ts(logpopdiff1)
plot.ts(logcocdiff1)
plot.ts(logimplant1diff1)
plot.ts(logimplant2diff1)
plot.ts(logiucddiff1)
plot.ts(loginjectablediff1)
```

**model diagnostics- Acf and Pacf plots**

```
par(mfrow=c(3,2))
acf(logcocdiff1, ylim=c(-1,1), main="ACF-Diff log COC")
pacf(logcocdiff1, ylim=c(-1,1), main="PACF-Diff log COC")
acf(logpopdiff1, ylim=c(-1,1), main="ACF-Diff log POP")
pacf(logpopdiff1, ylim=c(-1,1), main="PACF-Diff log POP")
acf(logimplant1diff1, ylim=c(-1,1), main="ACF-Diff log IMPLANT1")
pacf(logimplant1diff1, ylim=c(-1,1), main="PACF-Diff log IMPLANT1")
par(mfrow=c(3,2))
acf(logimplant2diff1, ylim=c(-1,1), main="ACF-Diff log IMPLANT2")
pacf(logimplant2diff1, ylim=c(-1,1), main="PACF-Diff log IMPLANT2")
acf(logiucddiff1, ylim=c(-1,1), main="ACF-Diff log IUCD")
pacf(logiucddiff1, ylim=c(-1,1), main="PACF-Diff log IUCD")
acf(loginjectablediff1, ylim=c(-1,1), main="ACF-Diff log INJECTABLE")
pacf(loginjectablediff1, ylim=c(-1,1), main="PACF-Diff log INJECTABLE")
```

**Forecasting of contraceptives**

**Auto.ARIMA Model**

```
auto.arima(logpop, max.p=15, max.q=15)
auto.arima (logcoc,  max.p=15, max.q=15)
auto.arima ( logimplant1,  max.p=15, max.q=15)
auto.arima (logimplant2,  max.p=15, max.q=15)
```

auto.arima (logiucd,  max.p=15, max.q=15)

auto.arima (loginjectable,  max.p=15, max.q=15)

**Stepwise**

auto.arima(logpop, stepwise=FALSE, approximation=FALSE)

auto.arima(logpop, stepwise=FALSE, approximation=FALSE, D=1)

auto.arima(logcoc, stepwise=FALSE, approximation=FALSE)

auto.arima(logcoc, stepwise=FALSE, approximation=FALSE, D=1)

auto.arima(logimplant1, stepwise=FALSE, approximation=FALSE)

auto.arima(logimplant1, stepwise=FALSE, approximation=FALSE, D=1)

auto.arima(logimplant2, stepwise=FALSE, approximation=FALSE)

auto.arima(logimplant2, stepwise=FALSE, approximation=FALSE, D=1)

auto.arima(logiucd, stepwise=FALSE, approximation=FALSE)

auto.arima(logiucd, stepwise=FALSE, approximation=FALSE, D=1)

auto.arima(loginjectable, stepwise=FALSE, approximation=FALSE)

auto.arima(loginjectable, stepwise=FALSE, approximation=FALSE, D=1)

**Model diagnostics**

contraceptives<-read.csv("C:/Users/PERP-PC/Desktop/Thesis proposal/doc/data/combined data with 2018.csv", header=TRUE)

**Generating the individual time series data**

coctimeseries<-ts(contraceptives$coc, frequency=12, start=2014)

poptimeseries<-ts(contraceptives$pop, frequency=12, start=2014)

implants1timeseries<-ts(contraceptives$implants1, frequency=12, start=2014)

implants2timeseries<-ts(contraceptives$implants2, frequency=12, start=2014)

iucdtimeseries<-ts(contraceptives$iucd, frequency=12, start=2014)

injectabletimeseries<-ts(contraceptives$injectable, frequency=12, start=2014)

**Generating log transformed series**

logcoc<-log(coctimeseries)

logpop<-log (poptimeseries)

logimplants1<-log (implants1timeseries)

logimplants2<-log (implants2timeseries)

```
logiucd<-log (iucdtimeseries)
loginjectable<-log (injectabletimeseries)
```
**Selecting window to allow out of sample evaluation for 2018**
```
windowlogcoc2018<-window(logcoc, start=c(2018,1), end=c(2018,6))
windowlogpop2018<-window(logpop, start=c(2018,1), end=c(2018,6))
windowlogimplants12018<-window(logimplants1, start=c(2018,1), end=c(2018,6))
windowlogimplants22018<-window(logimplants2, start=c(2018,1), end=c(2018,6))
windowlogiucd2018<-window(logiucd, start=c(2018,1), end=c(2018,6))
windowloginjectable2018<-window(loginjectable, start=c(2018,1), end=c(2018,6))
```
**Selecting a window to allow of out-of-sample validation**
```
windowlogcoc<-window(logcoc, start=c(2014,1), end=c(2017,12))
windowlogpop<-window(logpop, start=c(2014,1), end=c(2017,12))
windowlogimplants1<-window(logimplants1, start=c(2014,1), end=c(2017,12))
windowlogimplants2<-window(logimplants2, start=c(2014,1), end=c(2017,12))
windowlogiucd<-window(logiucd, start=c(2014,1), end=c(2017,12))
windowloginjectable<-window(loginjectable, start=c(2014,1), end=c(2017,12))
```
**Forecasting# install forecast package**

**ARIMA**

**POP**
```
arimapopA<-Arima(windowlogpop, order=c(1, 1, 0))
arimapopA
forecastpopA<-forecast(arimapopA,h=6)
forecastpopA
plot(forecastpopA,ylab="Units consumed", main="POP Forecast plots,ARIMA(1,1,0)")
lines(logpop, lwd=2)
lines(forecastpopA$mean, lwd=2, col="red")
summary(forecastpopA)
par(mfrow=c(1,2))
acf(arimapopA$resid, na.action=na.pass, ylim=c(-1,1))
```

```
pacf(arimapopA$resid, na.action=na.pass, ylim=c(-1,1))
Box.test(arimapopA$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
shapiro.test(arimapopA$resid)
```

**Overlaying the graphs-in sample/training**

```
plot(windowlogpop,main="Log POP with Fitted Lines")
lines(windowlogpop- arimapopA$resid, col="red")
```

**In-sample fit statistics**

```
accuracy(arimapopA)
```

**Out-of-sample forecast errors**

```
windowlogpop2018<-window(logpop, start=c(2018,1), end=c(2018,6))
accuracy(forecastpopA$mean, windowlogpop2018)
```

**COC**

```
arimacocA<-auto.arima(windowlogcoc, stepwise=FALSE, approximation=FALSE)
arimacocA
forecastcocA<-forecast(arimacocA,h=6)
forecastcocA
plot(forecastcocA,main="COC Forecast plots,ARIMA(0,1,1 with drift)")
lines(logcoc, lwd=2)
lines(forecastcocA$mean, lwd=2, col="red")
summary(forecastcocA)
par(mfrow=c(1,2))
acf(arimacocA$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimacocA$resid, na.action=na.pass, ylim=c(-1,1))
shapiro.test(arimacocA$resid)
Box.test(arimacocA$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
plot(windowlogcoc, main="Log COC with Fitted Lines")
lines(windowlogcoc- arimacocA$resid, col="red")
accuracy(arimacocA)
windowlogcoc2018<-window(logcoc, start=c(2018,1), end=c(2018,6))
```

```
accuracy(forecastcocA$mean, windowlogcoc2018)
```

**One rod implants**

```
arimaimplants1A<-Arima(windowlogimplants1, order=c(1, 1, 3))
arimaimplants1A
forecastimplants1A<-forecast(arimaimplants1A,h=6)
forecastimplants1A
plot(forecastimplants1A,main="ONE ROD IMPLANTS Forecast plots,ARIMA(1,1,3)")
lines(logimplants1, lwd=2)
lines(forecastimplants1A$mean, lwd=2, col="red")
summary(forecastimplants1A)
par(mfrow=c(1,2))
acf(arimaimplants1A$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimaimplants1A$resid, na.action=na.pass, ylim=c(-1,1))
shapiro.test(arimaimplants1A$resid)
Box.test(arimaimplants1A$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
plot(windowlogimplants1, main="Log ONE ROD IMPLANT with Fitted Lines")
lines(windowlogimplants1- arimaimplants1A$resid, col="red")
accuracy(arimaimplants1A)
windowlogimplants12018<-window(logimplants1, start=c(2018,1), end=c(2018,6))
accuracy(forecastimplants1A$mean, windowlogimplants12018)
```

*Part B*

```
arimaimplants1B<-Arima(windowlogimplants1, order=c(0, 1, 1))
arimaimplants1B
forecastimplants1B<-forecast(arimaimplants1B,h=6)
forecastimplants1B
plot(forecastimplants1B,main="ONE ROD IMPLANTS Forecast plots,ARIMA(0,1,1)")
lines(logimplants1, lwd=2)
lines(forecastimplants1B$mean, lwd=2, col="red")
summary(forecastimplants1B)
```

```
par(mfrow=c(1,2))
acf(arimaimplants1B$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimaimplants1B$resid, na.action=na.pass, ylim=c(-1,1))
shapiro.test(arimaimplants1B$resid)
Box.test(arimaimplants1B$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
plot(windowlogimplants1, main="Log ONE ROD IMPLANT with Fitted Lines")
lines(windowlogimplants1- arimaimplants1A$resid, col="red")
accuracy(arimaimplants1B)
windowlogimplants12018<-window(logimplants1, start=c(2018,1), end=c(2018,6))
accuracy(forecastimplants1B$mean, windowlogimplants12018)
```

**IUCDs**

```
arimaiucdA<-Arima(windowlogiucd, order=c(0, 1, 1))
arimaiucdA
forecastiucdA<-forecast(arimaiucdA,h=6)
forecastiucdA
plot(forecastiucdA,main="IUCD Forecast plots,ARIMA(0,1,1)")
lines(logiucd, lwd=2)
lines(forecastiucdA$mean, lwd=2, col="red")
summary(forecastiucdA)
par(mfrow=c(1,2))
acf(arimaiucdA$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimaiucdA$resid, na.action=na.pass, ylim=c(-1,1))
shapiro.test(arimaiucdA$resid)
Box.test(arimaiucdA$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
plot(windowlogiucd, main="Log IUCD with Fitted Lines")
lines(windowlogiucd- arimacocA$resid, col="red")
accuracy(arimaiucdA)
windowlogiucd2018<-window(logiucd, start=c(2018,1), end=c(2018,6))
accuracy(forecastiucdA$mean, windowlogiucd2018)
```

*Part B*

```
arimaiucdB<-Arima(windowlogiucd, order=c(2, 1, 0))
arimaiucdB
forecastiucdB<-forecast(arimaiucdB,h=6)
forecastiucdB
plot(forecastiucdB,main="IUCD Forecast plots,ARIMA(2,1,0)")
lines(logiucd, lwd=2)
lines(forecastiucdB$mean, lwd=2, col="red")
summary(forecastiucdB)
par(mfrow=c(1,2))
acf(arimaiucdB$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimaiucdB$resid, na.action=na.pass, ylim=c(-1,1))
shapiro.test(arimaiucdB$resid)
Box.test(arimaiucdB$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
plot(windowlogiucd, main="Log IUCD with Fitted Lines")
lines(windowlogiucd- arimaiucdA$resid, col="red")
accuracy(arimaiucdB)
windowlogiucd2018<-window(logiucd, start=c(2018,1), end=c(2018,6))
accuracy(forecastiucdB$mean, windowlogiucd2018)
```

**Two rod Implants**

```
arimaimplants2A<-Arima(windowlogimplants2, order=c(0, 1, 1))
arimaimplants2A
forecastimplants2A<-forecast(arimaimplants2A,h=6)
forecastimplants2A
plot(forecastimplants2A,main="TWO ROD IMPLANTS Forecast plots,ARIMA(0,1,1)")
lines(logimplants2, lwd=2)
lines(forecastimplants2A$mean, lwd=2, col="red")
summary(forecastimplants2A)
par(mfrow=c(1,2))
```

```
acf(arimaimplants2A$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimaimplants2A$resid, na.action=na.pass, ylim=c(-1,1))
shapiro.test(arimaimplants2A$resid)
Box.test(arimaimplants2A$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
plot(windowlogimplants2, main="Log Two rod Implants with Fitted Lines")
lines(windowlogimplants2- arimaimplants2A$resid, col="red")
accuracy(arimaimplants2A)
windowlogimplants22018<-window(logimplants2, start=c(2018,1), end=c(2018,6))
accuracy(forecastimplants2A$mean, windowlogimplants22018)
```

**Injectables**

```
arimainjectableA<-auto.arima(windowloginjectable, stepwise=FALSE, approximation=FALSE)
arimainjectableA
forecastinjectableA<-forecast(arimainjectableA,h=6)
forecastinjectableA
plot(forecastinjectableA,main="Injectable Forecast plots,ARIMA(5,1,0 with drift)")
lines(loginjectable, lwd=2)
lines(forecastinjectableA$mean, lwd=2, col="red")
summary(forecastinjectableA)
par(mfrow=c(1,2))
acf(arimainjectableA$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimainjectableA$resid, na.action=na.pass, ylim=c(-1,1))
shapiro.test(arimainjectableA$resid)
Box.test(arimainjectableA$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
plot(windowloginjectable, main="Log Injectable with Fitted Lines")
lines(windowloginjectable- arimainjectableA$resid, col="red")
accuracy(arimainjectableA)
windowloginjectable2018<-window(loginjectable, start=c(2018,1), end=c(2018,6))
accuracy(forecastinjectableA$mean, windowloginjectable2018)
```

*Part B*

```
arimainjectableB<-Arima(windowloginjectable, order=c(0, 1, 1))
arimainjectableB
forecastinjectableB<-forecast(arimainjectableB,h=6)
forecastinjectableB
summary(forecastinjectableB)
par(mfrow=c(1,2))
acf(arimainjectableB$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimainjectableB$resid, na.action=na.pass, ylim=c(-1,1))
shapiro.test(arimainjectableB$resid)
Box.test(arimainjectableB$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
plot(windowloginjectable, main="Log Injectable with Fitted Lines")
lines(windowloginjectable- arimainjectableB$resid, col="red")
accuracy(arimainjectableB)
windowloginjectable2018<-window(loginjectable, start=c(2018,1), end=c(2018,6))
accuracy(forecastinjectableB$mean, windowloginjectable2018)
```

**Combined plots for ARIMA**

```
par(mfrow=c(2,1))
plot(forecastpopA,xlab="Time",ylab=" Units consumed",main="(a)POP Forecast
plots,ARIMA(1,1,0)")
lines(logpop, lwd=2)
lines(forecastpopA$mean, lwd=2, col="red")
plot(forecastcocA,xlab="Time",ylab=" Units consumed",main="(b)COC Forecast
plots,ARIMA(0,1,1)")
lines(logcoc, lwd=2)
lines(forecastcocA$mean, lwd=2, col="red")
par(mfrow=c(2,1))
plot(forecastiucdA,xlab="Time",ylab=" Units consumed",main="(a)IUCD Forecast
plots,ARIMA(0,1,1)")
lines(logiucd, lwd=2)
lines(forecastiucdA$mean, lwd=2, col="red")
```

```
plot(forecastinjectableA,xlab="Time",ylab=" Units consumed",main="(b)Injectable Forecast plots,ARIMA(5,1,0 with drift)")

lines(loginjectable, lwd=2)

lines(forecastinjectableA$mean, lwd=2, col="red")

par(mfrow=c(2,1))

plot(forecastimplants1A,xlab="Time",ylab="Units consumed",main="(a)ONE ROD IMPLANTS Forecast plots,ARIMA(1,1,3)")

lines(logimplants1, lwd=2)

lines(forecastimplants1A$mean, lwd=2, col="red")

plot(forecastimplants2A,xlab="Time",ylab="Units consumed",main="(b)TWO ROD IMPLANTS Forecast plots,ARIMA(0,1,1)")

lines(logimplants2, lwd=2)

lines(forecastimplants2A$mean, lwd=2, col="red")
```

**Combining graphs for in sample estimates**

```
par(mfrow=c(3,2))

plot(windowlogpop, main="(a)Log POP with Fitted Lines")

lines(windowlogpop- arimapopA$resid, col="red")

plot(windowlogpop, main="(b)Log POP with Fitted Lines")

lines(windowlogpop- arimapopA$resid, col="red")

plot(windowlogimplants1, main="(c)Log ONE ROD IMPLANT with Fitted Lines")

lines(windowlogimplants1- arimaimplants1A$resid, col="red")

plot(windowlogimplants2, main="(d)Log Two rod Implants with Fitted Lines")

lines(windowlogimplants2- arimaimplants2A$resid, col="red")

plot(windowlogiucd, main="(e)Log IUCD with Fitted Lines")

lines(windowlogiucd- arimaiucdA$resid, col="red")

plot(windowloginjectable, main="(f)Log Injectable with Fitted Lines")

lines(windowloginjectable- arimainjectableA$resid, col="red")
```

**PACF and ACF combined plots**

```
par(mfrow=c(3,2))

acf(arimapopA$resid, na.action=na.pass, ylim=c(-1,1))

pacf(arimapopA$resid, na.action=na.pass, ylim=c(-1,1))
```

```
acf(arimaimplants1A$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimaimplants1A$resid, na.action=na.pass, ylim=c(-1,1))
acf(arimaimplants1A$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimaimplants1A$resid, na.action=na.pass, ylim=c(-1,1))
par(mfrow=c(3,2))
acf(arimaimplants2A$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimaimplants2A$resid, na.action=na.pass, ylim=c(-1,1))
acf(arimaimplants2A$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimaimplants2A$resid, na.action=na.pass, ylim=c(-1,1))
acf(arimainjectableB$resid, na.action=na.pass, ylim=c(-1,1))
pacf(arimainjectableB$resid, na.action=na.pass, ylim=c(-1,1))
```

**1. Exponential smoothing with underlying states space model**

**POP**

```
etspopA<-ets(windowlogpop)
etspopA
forecastpopA<-forecast(etspopA,h=6)
forecastpopA
plot(forecastpopA,main="POP Forecast plots,ETS(M,N,N)")
lines(logpop, lwd=2)
lines(forecastpopA$mean, lwd=2, col="red")
summary(forecastpopA)
par(mfrow=c(1,2))
acf(etspopA$resid, na.action=na.pass, ylim=c(-1,1))
pacf(etspopA$resid, na.action=na.pass, ylim=c(-1,1))
Box.test(etspopA$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
shapiro.test(etspopA$resid)
plot(windowlogpop, main="Log POP with Fitted Lines")
lines(windowlogpop- etspopA$resid, col="red")
accuracy(etspopA)
```

```
windowlogpop2018<-window(logpop, start=c(2018,1), end=c(2018,6))
accuracy(forecastpopA$mean, windowlogpop2018)
```

**COC**

```
etscocA<-ets(windowlogcoc)
etscocA
forecastcocA<-forecast(etscocA,h=6)
forecastcocA
plot(forecastcocA,main="COC Forecast plots,ETS(A,N,N)")
lines(logcoc, lwd=2)
lines(forecastcocA$mean, lwd=2, col="red")
summary(forecastcocA)
par(mfrow=c(1,2))
acf(etscocA$resid, na.action=na.pass, ylim=c(-1,1))
pacf(etscocA$resid, na.action=na.pass, ylim=c(-1,1))
Box.test(etscocA$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
shapiro.test(etscocA$resid)
plot(windowlogcoc, main="Log COC with Fitted Lines")
lines(windowlogcoc- etspopA$resid, col="red")
accuracy(etscocA)
windowlogcoc2018<-window(logcoc, start=c(2018,1), end=c(2018,6))
accuracy(forecastcocA$mean, windowlogcoc2018)
```

**IUCDs**

```
etsiucdA<-ets(windowlogiucd)
etsiucdA
forecastiucdA<-forecast(etsiucdA,h=6)
forecastiucdA
plot(forecastiucdA,main="IUCD Forecast plots,ETS(M,N,N)")
lines(logiucd, lwd=2)
lines(forecastiucdA$mean, lwd=2, col="red")
```

```
summary(forecastiucdA)
par(mfrow=c(1,2))
acf(etsiucdA$resid, na.action=na.pass, ylim=c(-1,1))
pacf(etsiucdA$resid, na.action=na.pass, ylim=c(-1,1))
Box.test(etsiucdA$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
shapiro.test(etsiucdA$resid)
plot(windowlogiucd, main="Log IUCD with Fitted Lines")
lines(windowlogiucd- etspopA$resid, col="red")
accuracy(etsiucdA)
windowlogiucd2018<-window(logiucd, start=c(2018,1), end=c(2018,6))
accuracy(forecastiucdA$mean, windowlogiucd2018)
```

**Injectables**

```
etsinjectableA<-ets(windowloginjectable)
etsinjectableA
forecastinjectableA<-forecast(etsinjectableA,h=6)
forecastinjectableA
plot(forecastinjectableA,main="Injectable Forecast plots,ETS(A,N,N)")
lines(loginjectable, lwd=2)
lines(forecastinjectableA$mean, lwd=2, col="red")
summary(forecastinjectableA)
par(mfrow=c(1,2))
acf(etsinjectableA$resid, na.action=na.pass, ylim=c(-1,1))
pacf(etsinjectableA$resid, na.action=na.pass, ylim=c(-1,1))
Box.test(etsinjectableA$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
shapiro.test(etsinjectableA$resid)
plot(windowloginjectable, main="Log Injectable with Fitted Lines")
lines(windowloginjectable- etsinjectableA$resid, col="red")
accuracy(etsinjectableA)
windowloginjectable2018<-window(loginjectable, start=c(2018,1), end=c(2018,6))
```

```
accuracy(forecastinjectableA$mean, windowloginjectable2018)
```

**One rod Implants**

```
etsimplants1A<-ets(windowlogimplants1)
etsimplants1A
forecastimplants1A<-forecast(etsimplants1A,h=6)
forecastimplants1A
plot(forecastimplants1A,main="One rod Implant Forecast plots,ETS(M,N,N)")
lines(logimplants1, lwd=2)
lines(forecastimplants1A$mean, lwd=2, col="red")
summary(forecastimplants1A)
par(mfrow=c(1,2))
acf(etsimplants1A$resid, na.action=na.pass, ylim=c(-1,1))
pacf(etsimplants1A$resid, na.action=na.pass, ylim=c(-1,1))
Box.test(etsimplants1A$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
shapiro.test(etsimplants1A$resid)
plot(windowlogimplants1, main="Log Implants1 with Fitted Lines")
lines(windowlogimplants1- etsimplants1A$resid, col="red")
accuracy(etsimplants1A)
windowlogimplants12018<-window(logimplants1, start=c(2018,1), end=c(2018,6))
accuracy(forecastimplants1A$mean, windowlogimplants12018)
```

**Two rod Implants**

```
etsimplants2A<-ets(windowlogimplants2)
etsimplants2A
forecastimplants2A<-forecast(etsimplants2A,h=6)
forecastimplants2A
plot(forecastimplants2A,main="Two rod Implant Forecast plots,ETS(A,A,N)")
lines(logimplants2, lwd=2)
lines(forecastimplants2A$mean, lwd=2, col="red")
summary(forecastimplants2A)
```

```
par(mfrow=c(1,2))
acf(etsimplants2A$resid, na.action=na.pass, ylim=c(-1,1))
pacf(etsimplants2A$resid, na.action=na.pass, ylim=c(-1,1))
Box.test(etsimplants2A$resid, lag = 1, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
shapiro.test(etsimplants2A$resid)
plot(windowlogimplants2, main="Log Implants2 with Fitted Lines")
lines(windowlogimplants2- etsimplants2A$resid, col="red")
accuracy(etsimplants2A)
windowlogimplants22018<-window(logimplants2, start=c(2018,1), end=c(2018,6))
accuracy(forecastimplants2A$mean, windowlogimplants22018)
```

**Combined plots - ETS**

```
par(mfrow=c(3,2))
plot(windowlogpop, main="(a)Log POP with Fitted Lines")
lines(windowlogpop- etspopA$resid, col="red")
plot(windowlogpop, main="(b)Log POP with Fitted Lines")
lines(windowlogpop- etspopA$resid, col="red")
plot(windowlogimplants1, main="(c)Log ONE ROD IMPLANT with Fitted Lines")
lines(windowlogimplants1- etsimplants1A$resid, col="red")
plot(windowlogimplants2, main="(d)Log Two rod Implants with Fitted Lines")
lines(windowlogimplants2- etsimplants2A$resid, col="red")
plot(windowlogiucd, main="(e)Log IUCD with Fitted Lines")
lines(windowlogiucd- etsiucdA$resid, col="red")
plot(windowloginjectable, main="(f)Log Injectable with Fitted Lines")
lines(windowloginjectable- etsinjectableA$resid, col="red")
```

**ACF and PACF plots- ETS**

```
par(mfrow=c(3,2))
acf(etspopA$resid, na.action=na.pass, ylim=c(-1,1))
pacf(etspopA$resid, na.action=na.pass, ylim=c(-1,1))
acf(etscocA$resid, na.action=na.pass, ylim=c(-1,1))
```

```
pacf(etscocA$resid, na.action=na.pass, ylim=c(-1,1))

acf(etsiucdA$resid, na.action=na.pass, ylim=c(-1,1))

pacf(etsiucdA$resid, na.action=na.pass, ylim=c(-1,1))

par(mfrow=c(3,2))

acf(etsimplants2A$resid, na.action=na.pass, ylim=c(-1,1))

pacf(etsimplants2A$resid, na.action=na.pass, ylim=c(-1,1))

acf(etsimplants2A$resid, na.action=na.pass, ylim=c(-1,1))

pacf(etsimplants2A$resid, na.action=na.pass, ylim=c(-1,1))

acf(etsinjectableA$resid, na.action=na.pass, ylim=c(-1,1))

pacf(etsinjectableA$resid, na.action=na.pass, ylim=c(-1,1))
```

**Combined plots for ETS**

```
par(mfrow=c(2,1))

plot(forecastpopA,xlab="Time",ylab=" Units consumed",main="(a)POP Forecast
plots,ETS(M,N,N)")

lines(logpop, lwd=2)

lines(forecastpopA$mean, lwd=2, col="red")

plot(forecastcocA,xlab="Time",ylab=" Units consumed",main="(b)COC Forecast
plots,ETS(A,N,N)")

lines(logcoc, lwd=2)

lines(forecastcocA$mean, lwd=2, col="red")

par(mfrow=c(2,1))

plot(forecastiucdA,xlab="Time",ylab=" Units consumed",main="(a)IUCD Forecast
plots,ETS(M,N,N)")

lines(logiucd, lwd=2)

lines(forecastiucdA$mean, lwd=2, col="red")

plot(forecastinjectableA,xlab="Time",ylab=" Units consumed",main="(b)Injectable Forecast
plots,ETS(A,N,N)")

lines(loginjectable, lwd=2)

lines(forecastinjectableA$mean, lwd=2, col="red")

par(mfrow=c(2,1))

lines(forecastinjectableA$mean, lwd=2, col="red")
```

```
plot(forecastimplants1A,xlab="Time",ylab=" Units consumed",main="(a)One rod Implant Forecast plots,ETS(M,N,N)")

lines(logimplants1, lwd=2)

lines(forecastimplants1A$mean, lwd=2, col="red")

plot(forecastimplants2A,xlab="Time",ylab=" Units consumed",main="(b)Two rod Implant Forecast plots,ETS(A,A,N)")

lines(logimplants2, lwd=2)

lines(forecastimplants2A$mean, lwd=2, col="red")
```

**Appendix B: Kenyatta National Hospital/University of Nairobi Ethics and Research Committee Approval**



**UNIVERSITY OF NAIROBI**
**COLLEGE OF HEALTH SCIENCES**
P O BOX 19676 Code 00202
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**KNH-UON ERC**
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**KENYATTA NATIONAL HOSPITAL**
P O BOX 20723 Code 00202
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Telegrams: MEDSUP, Nairobi

Ref: KNH-ERC/A/85

5th March, 2018

Karanja Perpetua Wanjiku
Reg. No.U51/87436/2016
Dept.of Pharmacology and Pharmacognosy
School of Pharmacy
College of Health Sciences
University of Nairobi

Dear Perpetua

**RESEARCH PROPOSAL – TIME SERIES ANALYSIS OF CONSUMPTION OF FAMILY PLANNING COMMODITIES IN THE PUBLIC SECTOR 2014 - 2017 (P714/12/2017)**

This is to inform you that the KNH- UoN Ethics & Research Committee (KNH- UoN ERC) has reviewed and **approved** your above revised proposal. The approval period is from 5th March 2018 – 4th March 2019.

This approval is subject to compliance with the following requirements:

a) Only approved documents (informed consents, study instruments, advertising materials etc) will be used.
b) All changes (amendments, deviations, violations etc) are submitted for review and approval by KNH-UoN ERC before implementation.
c) Death and life threatening problems and serious adverse events (SAEs) or unexpected adverse events whether related or unrelated to the study must be reported to the KNH-UoN ERC within 72 hours of notification.

d) Any changes, anticipated or otherwise that may increase the risks or affect safety or welfare of study participants and others or affect the integrity of the research must be reported to KNH- UoN ERC within 72 hours.
e) Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. (*Attach a comprehensive progress report to support the renewal*).
f) Submission of an *executive summary* report within 90 days upon completion of the study. This information will form part of the data base that will be consulted in future when processing related research studies so as to minimize chances of study duplication and/ or plagiarism.

For more details consult the KNH- UoN ERC website **http://www.erc.uonbi.ac.ke**

**Yours sincerely,**

**PROF. M.K. CHINDIA**
**SECRETARY, KNH-UoN ERC**

c.c. The Principal, College of Health Sciences, UoN
The Deputy Director, CS, KNH
The Chairperson, KNH-UON ERC
The Assistant Director, Health Information, KNH
The Dean, School of Pharmacy , UoN
The Chair, Dept. of Pharmacology and Pharmacognosy, UoN
Supervisors: Prof. Faith Okalebo, Dr. Mercy Mulaku, Dr. Levi Mbugua

**Appendix C: Summary of contraceptives consumption per year from 2014 to 2017 (Raw Data)**

| **FP commodity type** | **Combined Oral Contraceptives (COCs)** | **Progestin-Only Pills (POPs)** | **Injectables** | **Intrauterine Contraceptive Devices (IUCDs)** | **One –rod Implants** | **Two-rod Implants** |
|---|---|---|---|---|---|---|
| **Unit size/Year** | **Cycles** | | **Vials** | **Pieces** | **Pieces** | |
| 2014 | 1,453,061 | 232,021 | 2,937,647 | 366,757 | 208,621 | 117,099 |
| 2015 | 1,487,254 | 321,104 | 2,807,489 | 304,174 | 314,580 | 157,174 |
| 2016 | 1,181,608 | 321,370 | 2,546,368 | 259,757 | 357,065 | 192,955 |
| 2017 | 574,714 | 247,273 | 1,998,356 | 225,371 | 318,614 | 194,432 |
| Totals | 4,696,637 | 1,121,768 | 10,289,860 | 1,156,059 | 1,198,880 | 661,660 |
| Mean per year | 1,174,159 | 280442 | 2572465 | 289,015 | 299720 | 165,415 |
| Mean per month | 97,847 | 23,370 | 214,372 | 24,085 | 24,977 | 13,785 |

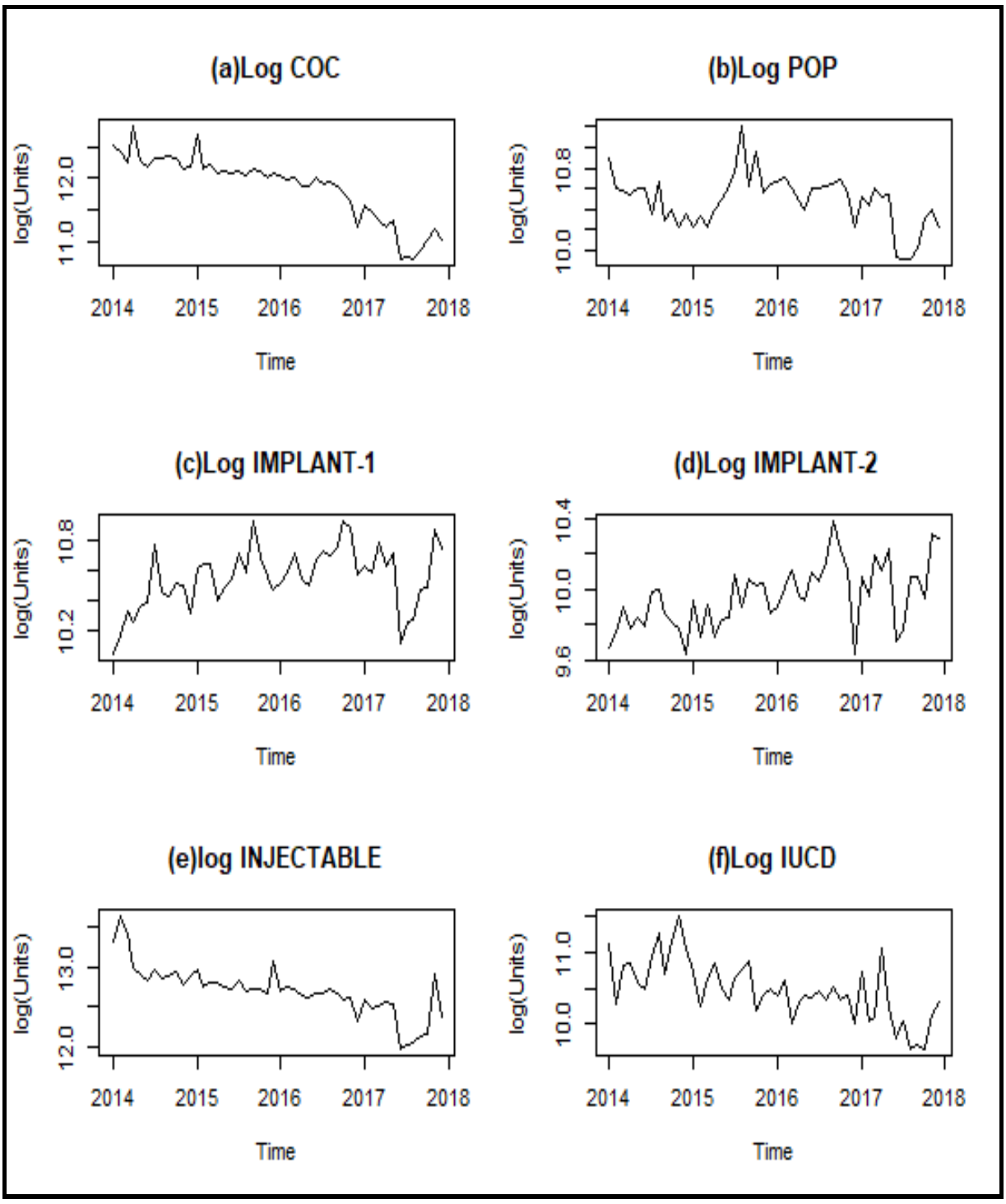
**Appendix D: Summary of contraceptives service point data per year from 2014 to 2017 (Raw Data)**

| | Number of clients who received contraceptives | | | | | |
|---|---|---|---|---|---|---|
| **Year** | **Combined Oral Contraceptives (COCs)** | **Progestin Only Pills (POPs)** | **Injectables** | **Intrauterine Contraceptive Devices(IUCDs)** | **Implants** | **Total number** |
| 2014 | 644,402 | 152,520 | 3,069,582 | 122,710 | 401,513 | 4,390,727 |
| 2015 | 616,138 | 171,142 | 2,938,361 | 125,805 | 513,757 | 4,365,203 |
| 2016 | 524,167 | 189,529 | 2,675,058 | 228,962 | 510,550 | 4,128,266 |
| 2017 | 289,113 | 138,509 | 2,034,587 | 217,997 | 491,137 | 3,171,343 |
| Totals | 2,073,820 | 651,700 | 10,717,588 | 695,474 | 1,916,957 | 16,055,539 |
| Mean per year | 518,455 | 162,925 | 2,679,397 | 173,869 | 479,239 | 4,013,885 |
| Mean per Month | 43,205 | 13,577 | 223,283 | 14,489 | 39,937 | 334,491 |

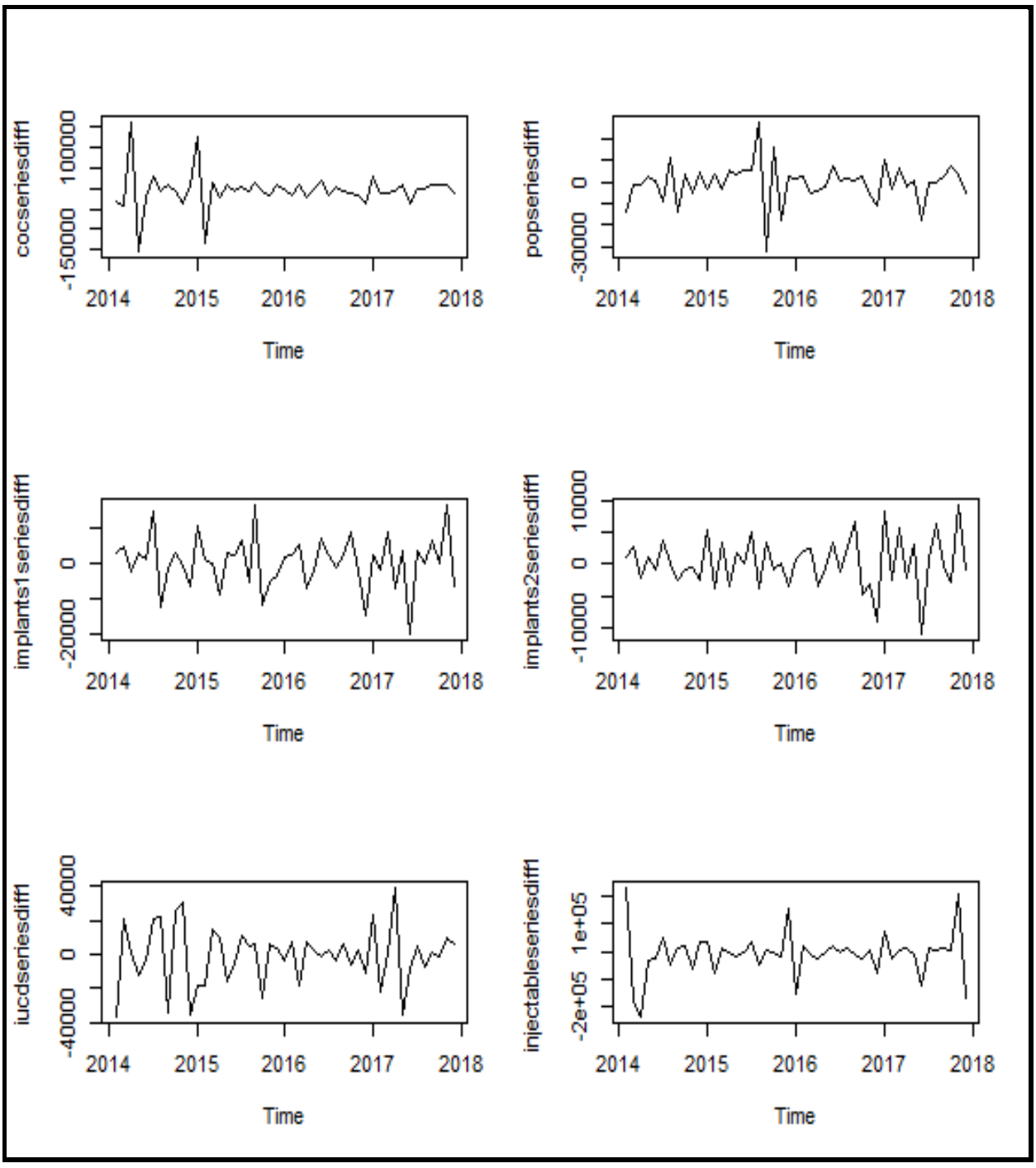
**Appendix E: Seasonal components of each family planning commodity**

| | Jan | Feb | March | April | May | June | July | Aug | Sept | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COC | 41466.4 | -6623.0 | 2117.5 | -11056.6 | -1975.3 | -7665.0 | -2826.9 | -1000.0 | 7629.4 | 5433.2 | -11557.3 | -13942.5 |
| POP | -1937.4 | -769.5 | -1187.7 | -1816.1 | -1345.1 | -3145.3 | 225.8 | 13807.3 | -1195.6 | 5893.0 | 3741.1 | -4788.2 |
| ONE ROD IMPLANTS | -1541.8 | -558.5 | 4249.4 | -3238.3 | -1975.9 | -6048.0 | 6063.3 | -636.6 | 4814.6 | 4304.0 | 1337.0 | -6769.2 |
| TWO ROD IMPLANTS | -293.9 | -1643.1 | 2081.2 | -965.8 | 267.1 | -2643.5 | 1867.2 | 1406.1 | 3741.3 | 1350.3 | -17.4 | -5149.5 |
| INJECTABLES | 18850.4 | -2341.1 | 7654.5 | 9807.6 | 1727.7 | -33114.3 | -3973.2 | -17989.3 | -737.4 | 5899.2 | -14185.1 | 28401.0 |
| IUCDS | -266.1 | -9789.2 | -9487.8 | 10446.8 | -4094.9 | -7717.0 | 442.4 | 8501.7 | 1561.5 | -344.8 | 12400.8 | -1653.6 |

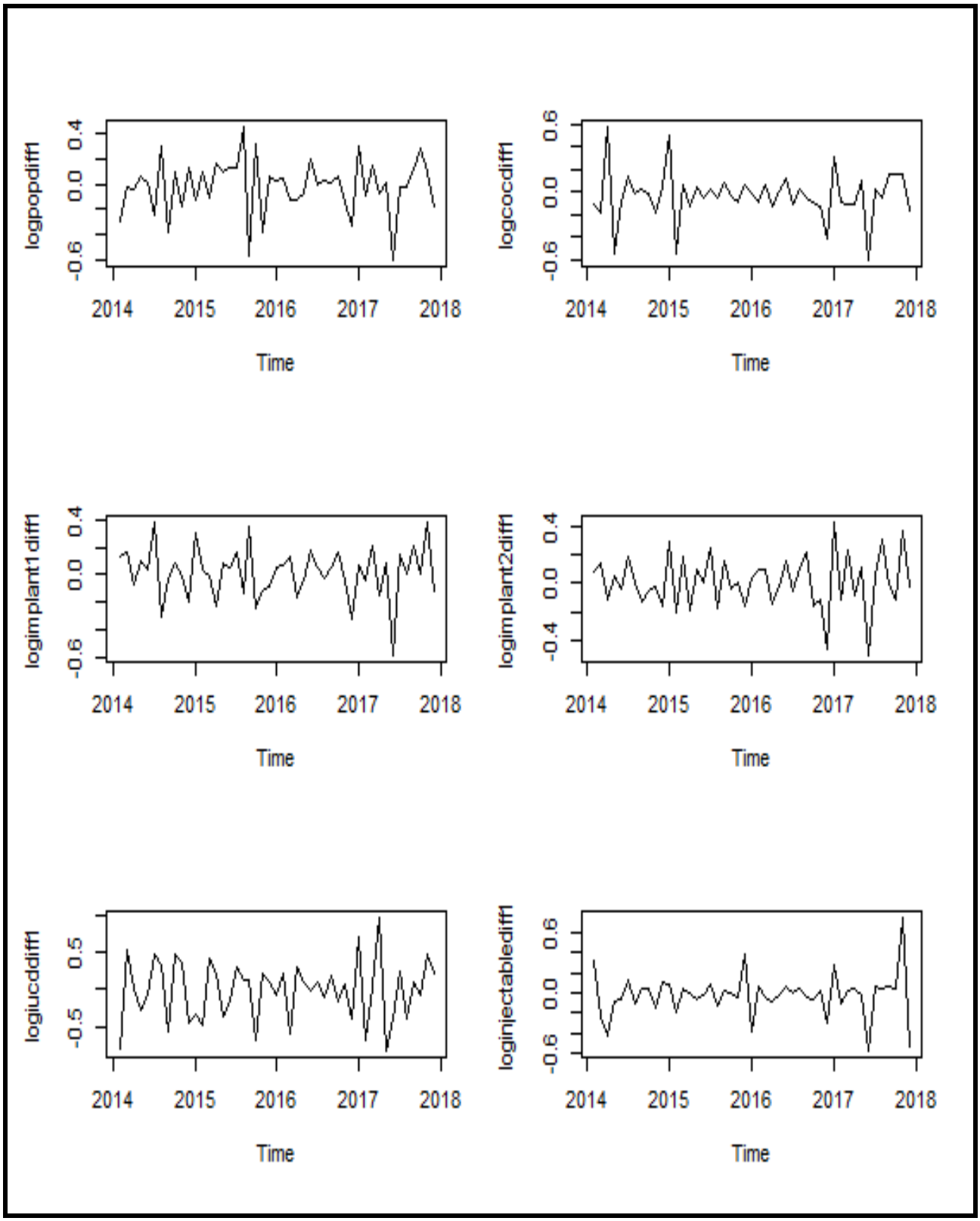
**Appendix F: Plots of log-transformed contraceptives data**



**Appendix G: Plots of differenced contraceptives data**



**Appendix H: Plots of transformed data (after differencing and log transformation)**



**Appendix I: In sample fit statistics**

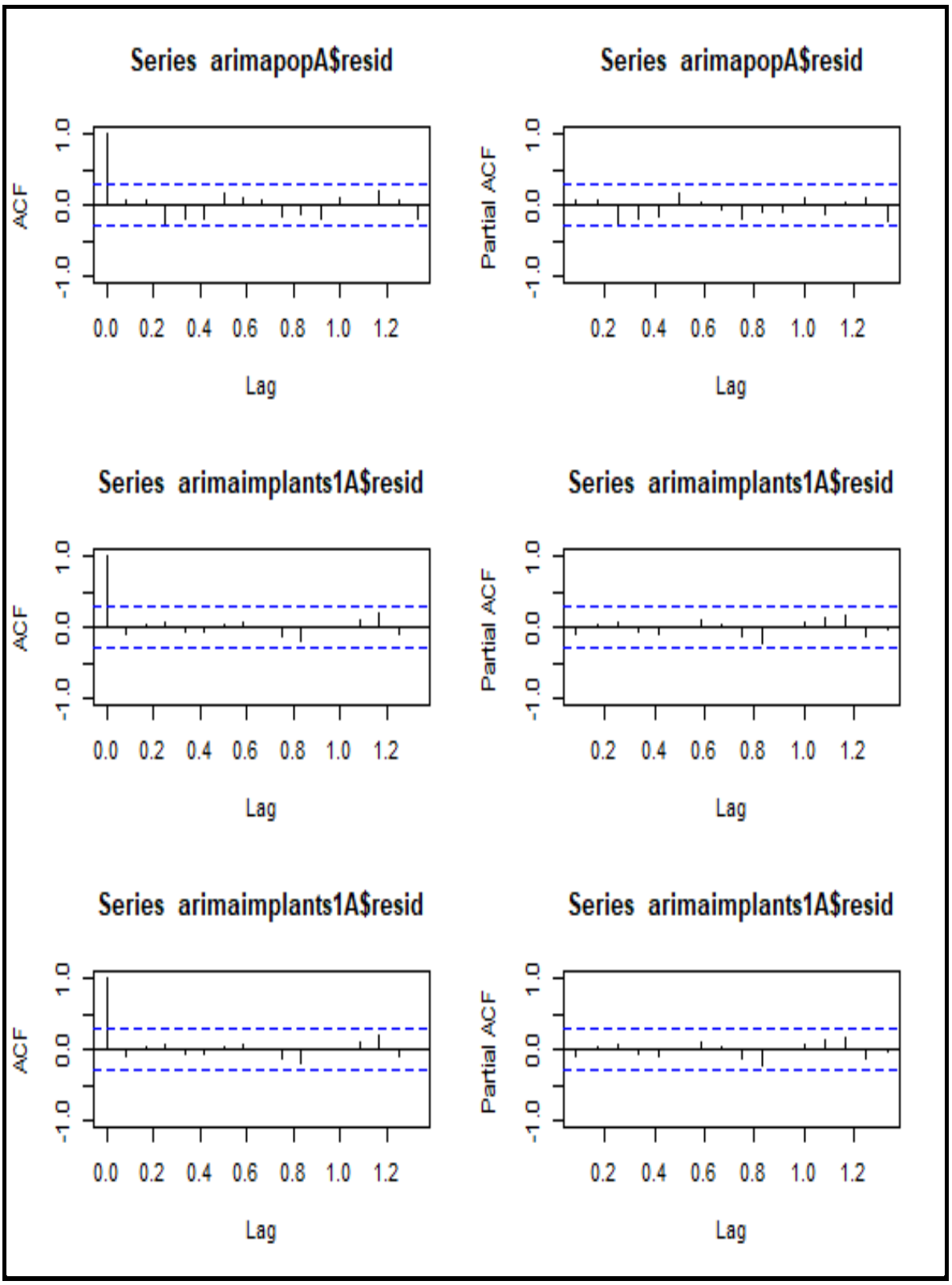
| FP METHOD | MODEL | ME | RMSE | MAE | MPE | MAPE | MASE | ACF1 |
|---|---|---|---|---|---|---|---|---|
| POP | ARIMA(1,1,0) | -0.0176 | 0.1952 | 0.1472 | -0.1892 | 1.4085 | 0.4987 | 0.0658 |
| | ETS(M,N,N) | 0.0169 | 0.1995 | 0.1525 | -0.1853 | 1.4577 | 0.5166 | -0.0676 |
| COC | ARIMA(0,1,1) with drift | -0.0004 | 0.1856 | 0.1243 | -0.0287 | 1.0593 | 0.2990 | 0.0147 |
| | ETS(A,N,N) | -0.0520 | 0.1952 | 0.1341 | -0.4621 | 1.1416 | 0.3225 | -0.1103 |
| IUCD | ARIMA(0,1,1) | -0.0651 | 0.3335 | 0.2631 | -0.7094 | 2.5250 | 0.6877 | 0.0462 |
| | ETS(M,N,N) | -0.0607 | 0.3334 | 0.2670 | -0.6708 | 2.5596 | 0.6980 | 0.0268 |
| Injectables | ARIMA(5,0,1) with drift | -0.0038 | 0.1645 | 0.1106 | -0.0410 | 0.8685 | 0.4284 | -0.0991 |
| | ETS(A,N,N) | -0.0337 | 0.1985 | 0.1227 | -0.2781 | 0.9658 | 0.4754 | -0.0045 |
| One rod Implant | ARIMA(1,1,3 | 0.0282 | 0.1497 | 0.1148 | 0.2562 | 1.0872 | 0.5764 | -0.0760 |
| | ETS(M,N,N) | 0.0206 | 0.1734 | 0.1293 | 0.1789 | 1.2247 | 0.6491 | 0.0133 |
| Two rod Implants | ARIMA(0,1,1) | 0.0349 | 0.1610 | 0.1216 | 0.3285 | 1.2196 | 0.6581 | 0.1176 |
| | ETS(A,A,N) | -0.0003 | 0.1489 | 0.1142 | -0.0250 | 1.1481 | 0.6179 | 0.1991 |

**Appendix J: Point forecasts for the contraceptives for the six-month forecast for the ARIMA model**

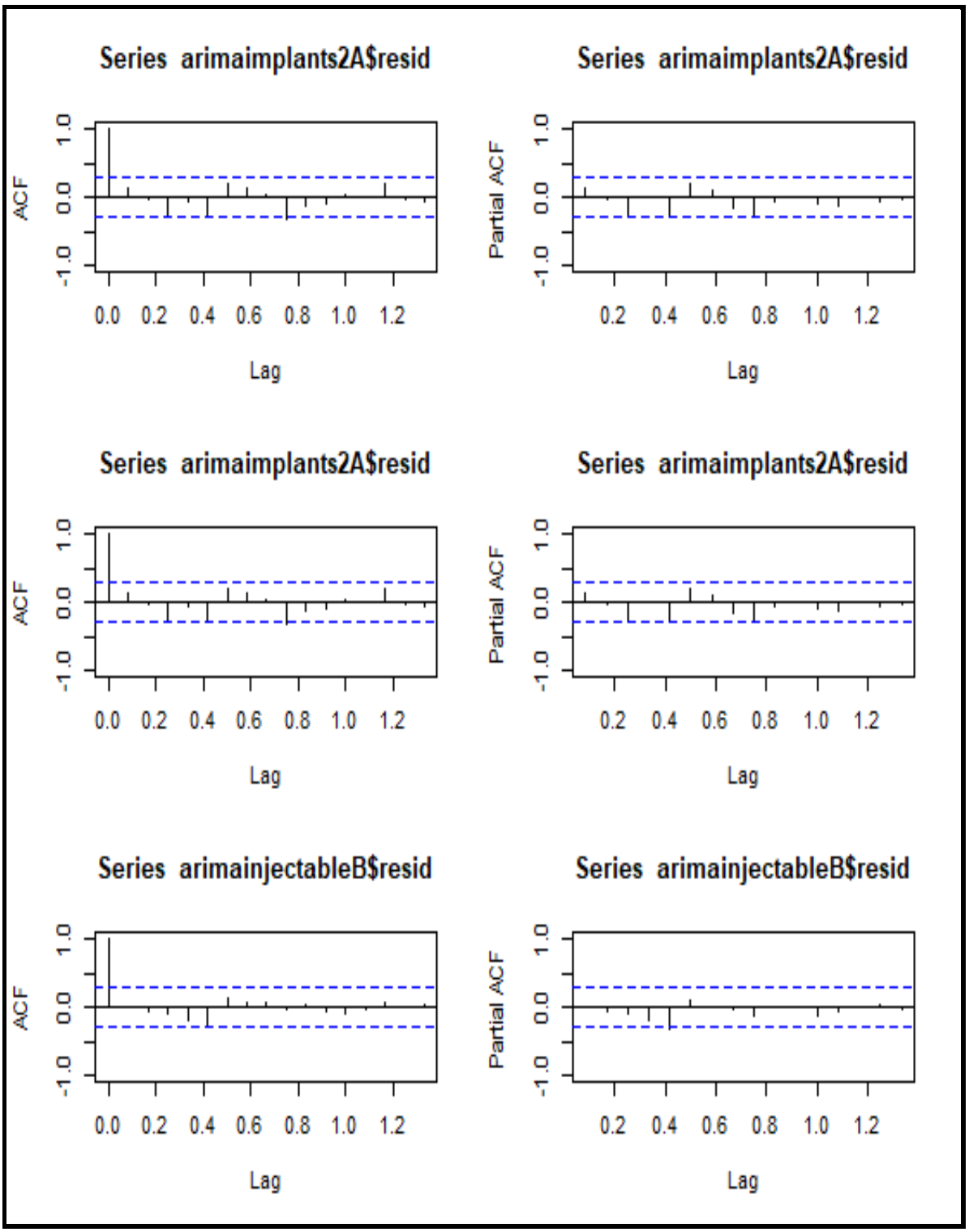
| Period | | Point forecasts | Lo.80 | Hi.80 | Lo.95 | Hi.95 |
|---|---|---|---|---|---|---|
| **POPs, ARIMA(1,1,0)** | | | | | | |
| January | 2018 | 10.29592 | 10.04033 | 10.55151 | 9.905023 | 10.68682 |
| February | 2018 | 10.26469 | 9.968446 | 10.56093 | 9.811624 | 10.71775 |
| March | 2018 | 10.27762 | 9.923734 | 10.63151 | 9.736398 | 10.81884 |
| April | 2018 | 10.27227 | 9.877277 | 10.66725 | 9.668182 | 10.87635 |
| May | 2018 | 10.27448 | 9.839179 | 10.70979 | 9.608743 | 10.94022 |
| June | 2018 | 10.27356 | 9.802572 | 10.74456 | 9.553244 | 10.99389 |
| **COCs, ARIMA (0,1,1) with drift** | | | | | | |
| Jan | 2018 | 10.96766 | 10.72204 | 11.21328 | 10.59202 | 11.3433 |
| Feb | 2018 | 10.93571 | 10.66831 | 11.20312 | 10.52676 | 11.34467 |
| Mar | 2018 | 10.90377 | 10.61623 | 11.19131 | 10.46401 | 11.34352 |
| Apr | 2018 | 10.87182 | 10.56546 | 11.17818 | 10.40328 | 11.34036 |
| May | 2018 | 10.83988 | 10.51579 | 11.16396 | 10.34423 | 11.33553 |
| Jun | 2018 | 10.80793 | 10.46703 | 11.14882 | 10.28658 | 11.32928 |
| **IMPLANTS, ARIMA (1,1,3)** | | | | | | |
| January | 2018 | 10.68119 | 10.47847 | 10.88391 | 10.37116 | 10.99123 |
| February | 2018 | 10.57267 | 10.30455 | 10.84078 | 10.16261 | 10.98272 |
| March | 2018 | 10.62027 | 10.32891 | 10.91164 | 10.17467 | 11.06588 |
| April | 2018 | 10.58062 | 10.2866 | 10.87463 | 10.13096 | 11.03027 |

| | | | | | | |
|---|---|---|---|---|---|---|
| May | 2018 | 10.61365 | 10.30258 | 10.92472 | 10.13791 | 11.08938 |
| June | 2018 | 10.58613 | 10.27111 | 10.90116 | 10.10435 | 11.06792 |
| **IUCDs, ARIMA(0,1,1)** | | | | | | |
| January | 2018 | 10.03936 | 9.602801 | 10.47593 | 9.371699 | 10.70703 |
| February | 2018 | 10.03936 | 9.587364 | 10.49136 | 9.348091 | 10.73064 |
| March | 2018 | 10.03936 | 9.572438 | 10.50629 | 9.325262 | 10.75346 |
| April | 2018 | 10.03936 | 9.557974 | 10.52075 | 9.303142 | 10.77559 |
| May | 2018 | 10.03936 | 9.543932 | 10.53479 | 9.281666 | 10.79706 |
| June | 2018 | 10.03936 | 9.530277 | 10.54845 | 9.260783 | 10.81794 |
| **TWO ROD IMPLANTS, ARIMA(0,1,1)** | | | | | | |
| January | 2018 | 10.11405 | 9.903219 | 10.32488 | 9.791612 | 10.43649 |
| February | 2018 | 10.11405 | 9.897899 | 10.3302 | 9.783477 | 10.44462 |
| March | 2018 | 10.11405 | 9.892708 | 10.33539 | 9.775537 | 10.45256 |
| April | 2018 | 10.11405 | 9.887636 | 10.34046 | 9.76778 | 10.46032 |
| May | 2018 | 10.11405 | 9.882674 | 10.34542 | 9.760192 | 10.4679 |
| June | 2018 | 10.11405 | 9.877817 | 10.35028 | 9.752764 | 10.47533 |
| **INJECTABLES, ARIMA (5,0,1) with drift** | | | | | | |
| January | 2018 | 12.28698 | 12.05886 | 12.51511 | 11.93809 | 12.63587 |
| February | 2018 | 12.14053 | 11.88088 | 12.40018 | 11.74344 | 12.53762 |
| March | 2018 | 11.9424 | 11.65948 | 12.22532 | 11.50971 | 12.37508 |
| April | 2018 | 11.78575 | 11.49063 | 12.08086 | 11.33441 | 12.23708 |
| May | 2018 | 12.26559 | 11.9695 | 12.56169 | 11.81275 | 12.71843 |
| June | 2018 | 12.19483 | 11.8962 | 12.49346 | 11.73811 | 12.65154 |

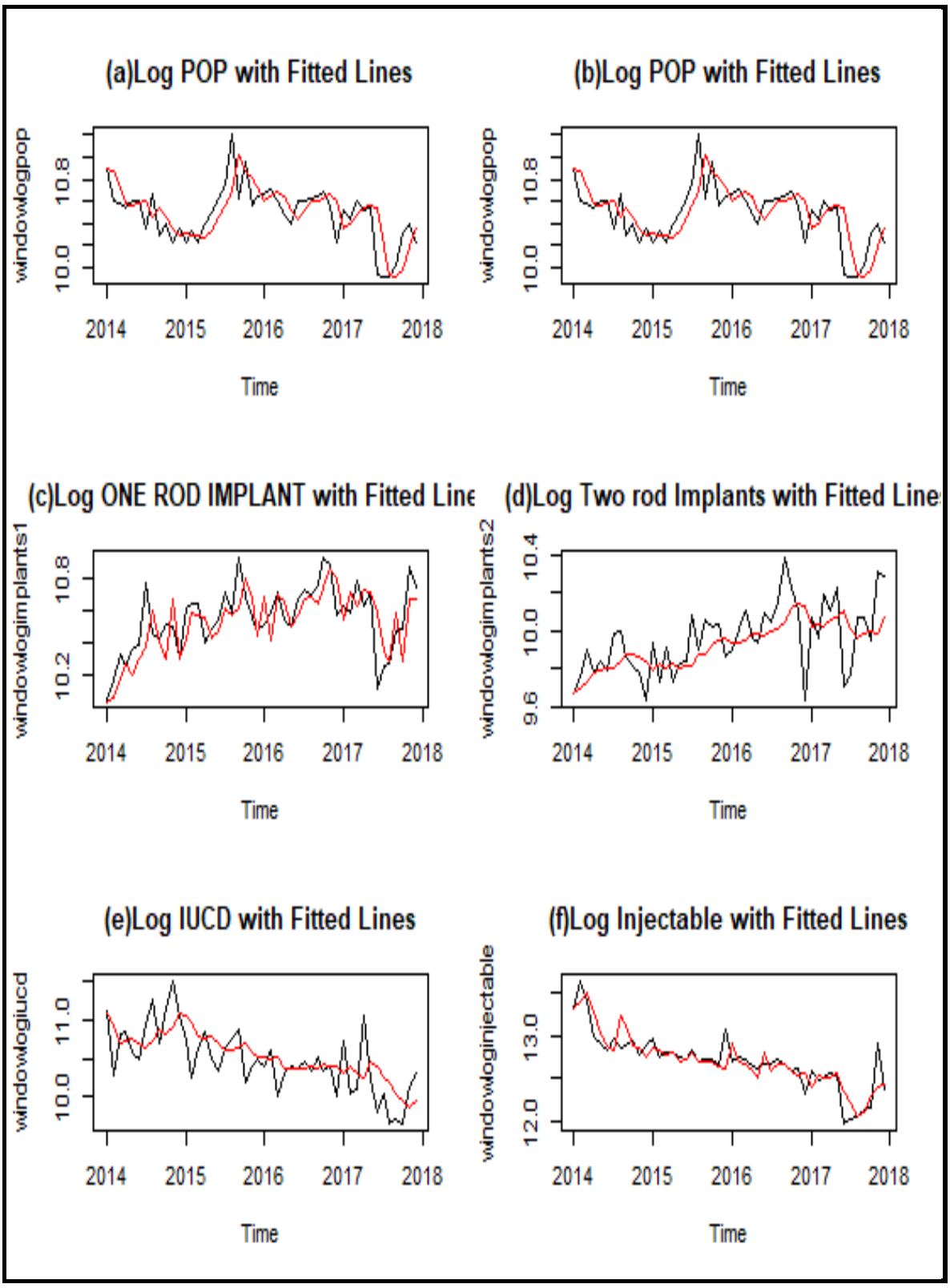
**Appendix K: ACF and pACF plots of residuals for POP's, COC's and IUCDs**



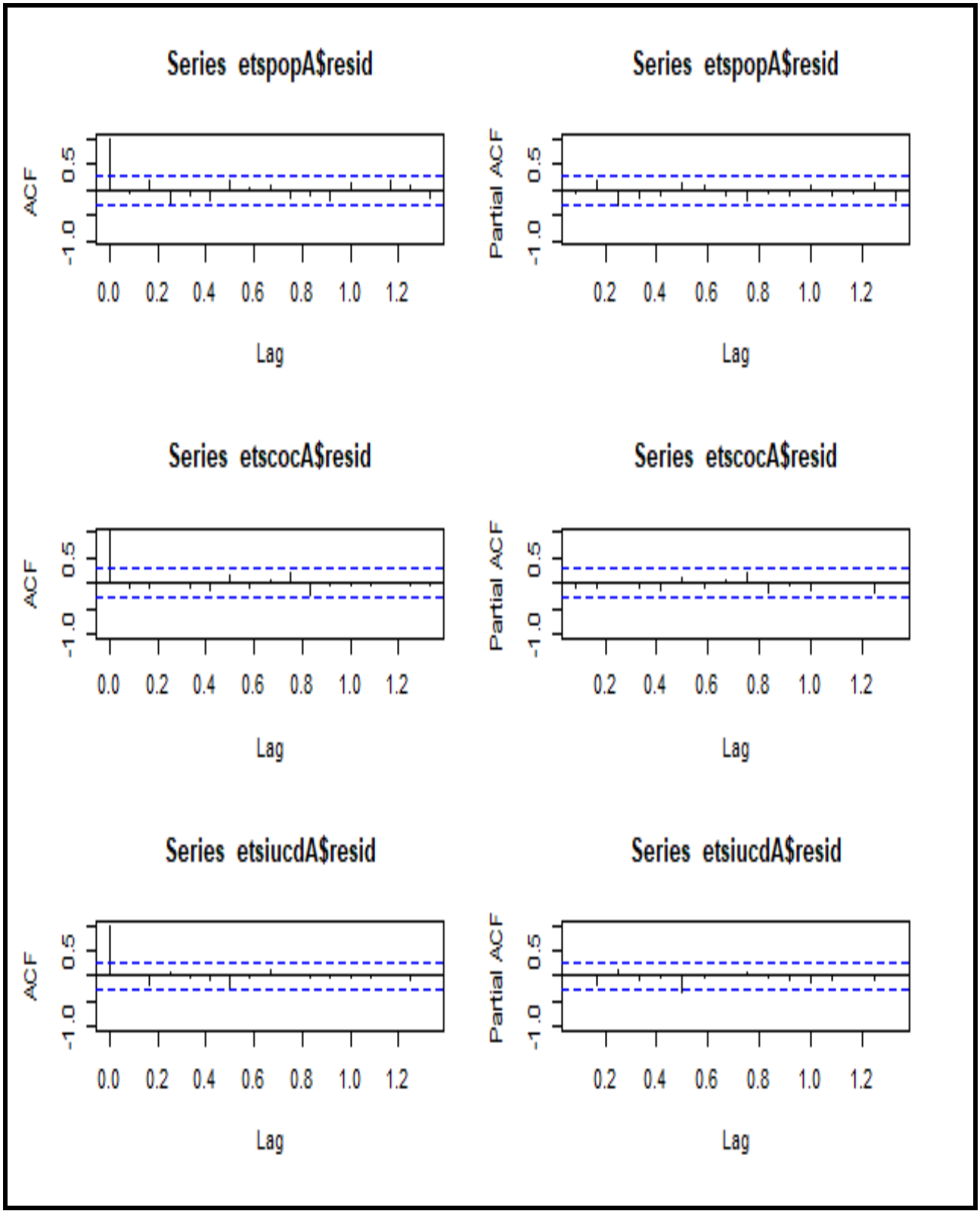
**Appendix L: ACF and PACF of residuals for ARIMA models**



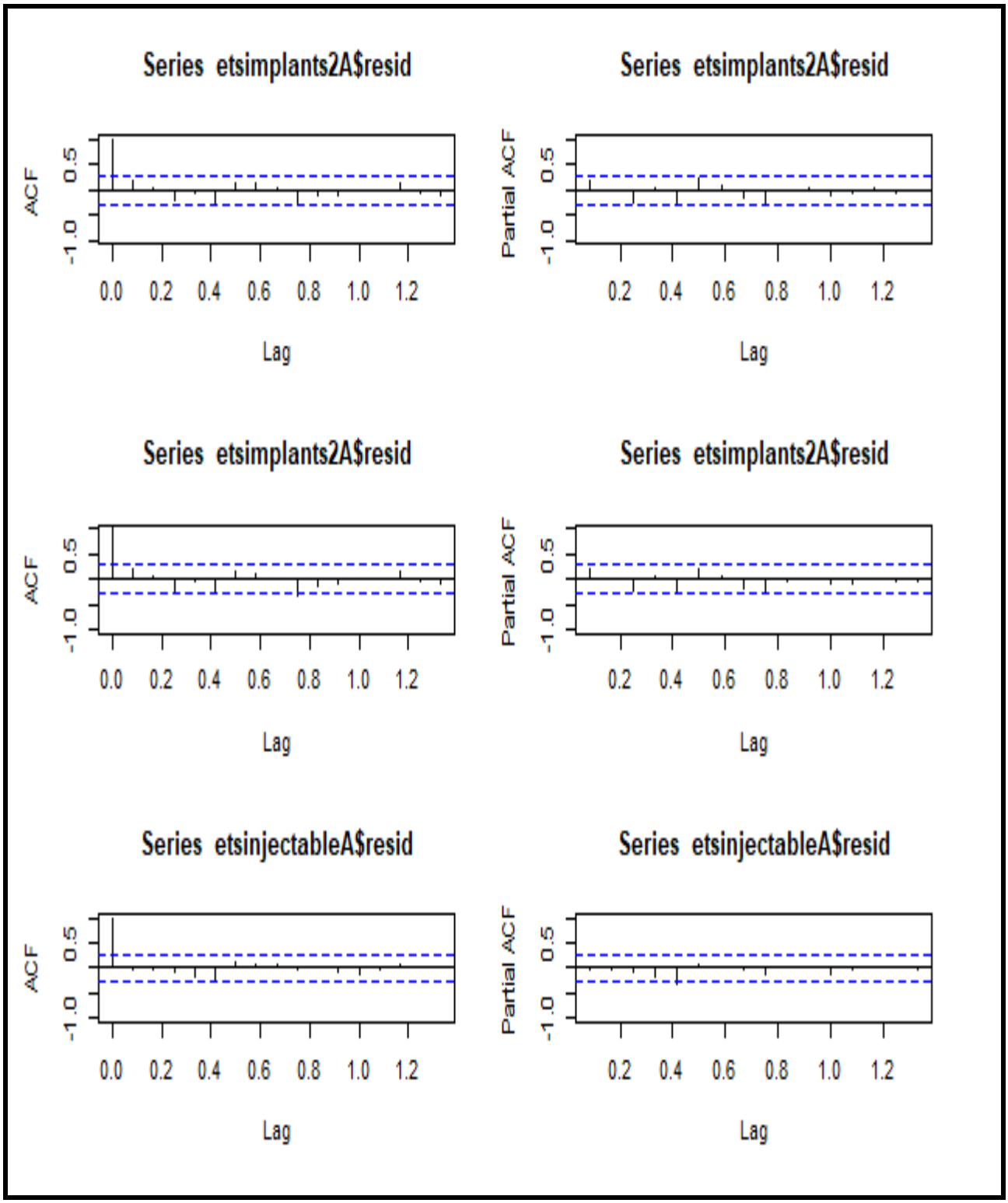
**Appendix M: Overlaid forecasting residuals on actual consumption for ARIMA models**



**Appendix N: ACF and PACF plots for exponential smoothing model residuals**



**Appendix O: ACF and PACF plots for exponential smoothing model residuals**



**Appendix P: Point Forecasts for the exponential smoothing method with underlying state space models**

| Period | | Point forecasts | Lo.80 | Hi.80 | Lo.95 | Hi.95 |
|---|---|---|---|---|---|---|
| **POPs, ETS (M,N,N)** | | | | | | |
| January | 2018 | 10.25901 | 10.010759 | 10.50725 | 9.879345 | 10.63867 |
| February | 2018 | 10.25901 | 9.962077 | 10.55594 | 9.804892 | 10.71312 |
| March | 2018 | 10.25901 | 9.920316 | 10.5977 | 9.741024 | 10.77699 |
| April | 2018 | 10.25901 | 9.883161 | 10.63485 | 9.684201 | 10.83381 |
| May | 2018 | 10.25901 | 9.849357 | 10.66865 | 9.632503 | 10.88551 |
| June | 2018 | 10.25901 | 9.818134 | 10.69988 | 9.58475 | 10.93326 |
| **COCs, ETS (A,N,N)** | | | | | | |
| January | 2018 | 11.05684 | 10.80664 | 11.30703 | 10.6742 | 11.43947 |
| February | 2018 | 11.05684 | 10.76892 | 11.34475 | 10.61651 | 11.49716 |
| March | 2018 | 11.05684 | 10.7356 | 11.37807 | 10.56555 | 11.54813 |
| April | 2018 | 11.05684 | 10.70542 | 11.40825 | 10.5194 | 11.59428 |
| May | 2018 | 11.05684 | 10.67764 | 11.43603 | 10.47691 | 11.63677 |
| June | 2018 | 11.05684 | 10.65176 | 11.46191 | 10.43732 | 11.67635 |
| **IUCDs, ETS (M,N,N)** | | | | | | |
| January | 2018 | 10.03972 | 9.632945 | 10.4465 | 9.417609 | 10.66184 |
| February | 2018 | 10.03972 | 9.619651 | 10.4598 | 9.397278 | 10.68217 |
| March | 2018 | 10.03972 | 9.606764 | 10.47268 | 9.377569 | 10.70188 |
| April | 2018 | 10.03972 | 9.594249 | 10.4852 | 9.358429 | 10.72102 |
| May | 2018 | 10.03972 | 9.582075 | 10.49737 | 9.339811 | 10.73964 |

| | | | | | | |
|---|---|---|---|---|---|---|
| June | 2018 | 10.03972 | 9.570216 | 10.50923 | 9.321674 | 10.75777 |
| **Injectables, ETS (A, N, N)** | | | | | | |
| January | 2018 | 12.45737 | 12.20294 | 12.71181 | 12.06825 | 12.84649 |
| February | 2018 | 12.45737 | 12.16381 | 12.75094 | 12.00841 | 12.90634 |
| March | 2018 | 12.45737 | 12.12931 | 12.78543 | 11.95565 | 12.9591 |
| April | 2018 | 12.45737 | 12.09811 | 12.81663 | 11.90793 | 13.00682 |
| May | 2018 | 12.45737 | 12.06942 | 12.84533 | 11.86404 | 13.05071 |
| June | 2018 | 12.45737 | 12.0427 | 12.87205 | 11.82318 | 13.09157 |
| **One-rod implants, ETS (M, N, N)** | | | | | | |
| January | 2018 | 10.72171 | 10.49584 | 10.94758 | 10.37628 | 11.06714 |
| February | 2018 | 10.72171 | 10.4554 | 10.98802 | 10.31443 | 11.12899 |
| March | 2018 | 10.72171 | 10.42033 | 11.02309 | 10.2608 | 11.18263 |
| April | 2018 | 10.72171 | 10.38894 | 11.05448 | 10.21278 | 11.23064 |
| May | 2018 | 10.72171 | 10.36026 | 11.08316 | 10.16892 | 11.2745 |
| June | 2018 | 10.72171 | 10.33369 | 11.10973 | 10.12828 | 11.31514 |
| **Two-rod implants, ETS A, A, N** | | | | | | |
| January | 2018 | 10.13742 | 9.946543 | 10.3283 | 9.845499 | 10.42934 |
| February | 2018 | 10.14471 | 9.953834 | 10.33559 | 9.85279 | 10.43663 |
| March | 2018 | 10.152 | 9.961125 | 10.34288 | 9.860081 | 10.44392 |
| April | 2018 | 10.15929 | 9.968416 | 10.35017 | 9.867371 | 10.45121 |
| May | 2018 | 10.16658 | 9.975706 | 10.35746 | 9.874662 | 10.45851 |
| June | 2018 | 10.17387 | 9.982997 | 10.36475 | 9.881953 | 10.4658 |

**Appendix Q: Overlaid forecasting residuals on actual consumption for ETS models**