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ADULTS NEWLY INFECTED WITH HIV IN RWANDA: A BOX-JENKINS ARIMA APPROACH

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Abstract:

Based on annual time series data on the number of adults (ages 15 and above) newly infected with HIV in Rwanda from 1990 – 2018, the study predicts the annual number of adults who will be newly infected with HIV over the period 2019 – 2030. The study will apply the Box-Jenkins ARIMA methodology. The presented diagnostic tests show that the H series under consideration is a stationary variable. Hinged on the AIC, the study presents the ARIMA (1, 0, 3) model as the parsimonious model. The residual correlogram further reveals that the presented model is stable. The results of the study indicate that the number of new HIV infections in adults in Rwanda is likely to increase from 3107 in 2019 to almost 5704 new infections by 2030. Even though Rwanda's national HIV programme has been touted as successful, our model shows that the gains of this noble programme are slowly being reversed; and by 2030, Rwanda will face a more serious challenge of HIV if no action is taken, now. Amongst other policy recommendations, the study basically encourages the government of Rwanda to continue scaling up HIV prevention and treatment activities throughout the country.

1.0INTRODUCTION

Bordered by Uganda, Tanzania, Burundi and the Democratic Republic of Congo (DRC), Rwanda is a landlocked country in the Great Lakes region of East Africa. The country has a predominantly dense and rural population. The average age of Rwandans is approximately 22.7 years (NISR, 2014). Growing at a rate of 2.6% per annum from 2002 to 2012, the country's total population is projected to reach 13.3 million by 2022 (Nsanzimana et al., 2015). HIV infection is a major public health concern in Rwanda, where it is one of the main causes of mortality, and carries negative social and economic consequences that affect everyone in the country (Hong et al., 2013).

HIV was first reported in Rwanda in 1983 by a team of Belgian scientists (ibid). In 1986, Rwanda conducted its first population-based sero-prevalence survey that reported an urban prevalence of 18% and a rural prevalence of 1% (Dunn, 1989). For almost 10 years after, there was little awareness of HIV/AIDS, and most physicians were unable to recognize,

diagnose or treat the condition. People living with HIV were kept in isolation wards with poor sanitary conditions and without safety precautions to prevent transmission between patients and hospital staff. There was little to no access to HIV treatment in Rwanda prior to 1994 (Nsanzimana et al., 2015). The 1994 genocide significantly set back all of Rwanda's development efforts. In the wake of the 100-days of killing, 2 million were left homeless and the health system had collapsed (Nowrojee, 1996). Rape, as a weapon of war, was used against more than 250000 women and helped fuel a sharp increase in HIV infections after the genocide (ibid).

At least 3% of Rwandan adults aged 15-49 are infected with HIV. The prevalence is much higher in urban areas, among women and among adults who have had multiple sexual partners (Hong et al., 2013). As in other countries in Sub-Saharan Africa (SSA), the majority of new HIV infections in Rwanda are the result of heterosexual transmission in the adult population (Dunkle et al., 2008). Fortunately, the country has now achieved high rates of ART coverage, accounting 164262 (78%) of all people living with HIV in 2016 and 93% of retention in care after 12 months on treatment due to the success of Rwanda's national HIV programme (Nsanzimana et al., 2017; Biraguma et al., 2018). The main goal of this paper is to predict the number of adults newly infected with HIV in Rwanda over the period 2019 – 2030. This study will go a long way in assessing the possibility of ending the HIV scourge in Rwanda.

2.0 LITERATURE REVIEW

Bendavid et al. (2016) combined demographic, epidemiologic and health services data in order to estimate mortality along the continuum of HIV care in Rwanda. The study was based on a calibrated age-structured HIV disease and transmission stochastic simulation model. The study indicated that most HIV-related deaths occurred among those untested, followed by those on ART. This implies that in Rwanda, there still many people who have HIV but do not know their status and this continues to be the life of others at risk. This can potentially lead to a resurgence of HIV infections in the country. In another Rwandan study, Mwumvaneza et al. (2017) examined the incidence of HIV in Rwanda. Based on two-stage sampling over the period 2013-14, the authors carried out a prospective HIV incidence survey in 492 randomly selected villages. The study results indicated that the incidence of HIV in Rwanda was very high. Consistently, Ingabire et al. (2019) recruited Female Sex Workers (FSW) from known hotspots in Kigali, Rwanda, and offered free, anonymous HIV counseling and testing, diagnosis and treatment of Sexually Transmitted Infections (STIs) and Long-Acting Reversible Contraception (LARC) over the period September 2012 to March 2015. The study found out that: the prevalence of serologic syphilis was 43% in HIV-positive and 19% in HIV-negative FSWs, and Trichomonas vaginalis was found in viginal wet mounts in 21% of HIV-positive and 13% of HIV-negative FSWs. Only one-third

reported consistent condom use. The overall conclusion of the study was that the prevalence of HIV – including in many new cases – and STIs among FSWs in Kigali was high and that condom use was low. Low levels of condom use basically imply a possible resurge in new HIV infections in Rwanda and this warranties the need for modeling and forecasting new HIV infections in order to empirically verify the trends of new HIV infections in the country. Similarly, Adedimeji et al. (2019) carried out a study on the prevalence of risky sexual practices of Rwandan MSM and the concomitant socio-contextual determinants using an explorative qualitative design. The study found out that risky sexual practices were common, and that the knowledge of STIs was poor, but prevalence, especially of HPV was high. This paper ironically tells us that it is possible to see rise in new HIV infections in Rwanda in the near future. However, no study has attempted to model and forecast new HIV infections in the country. This study will focus on new HIV infections in adults because the HIV epidemic in Rwanda is largely skewed towards adults than children in the country.

3.0 METHODODOLOGY

3.1 The Box – Jenkins (1970) Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018c). This approach will be used to analyze the H series under consideration.

3.2 The Moving Average (MA) model

Given:

$$H_t = \sum_{i=1}^{q} \alpha_i \mu_{t-i} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots [1]$$

where μ_t is a purely random process with mean zero and varience σ^2. Equation [1] is reffered to as a Moving Average (MA) process of order q, commonly denoted as MA (q). H is the annual number of adults newly infected with HIV in Rwanda at time t, $\alpha_0 \dots \alpha_q$ are estimation parameters, μ_t is the current error term while $\mu_{t-1} \dots \mu_{t-q}$ are previous error terms.

3.3 The Autoregressive (AR) model

Given:

$$H_t = \sum_{i=1}^{p} \beta_i H_{t-i} + \mu_t \quad \ldots\ldots [2]$$

Where $\beta_1 \ldots \beta_p$ are estimation parameters, $H_{t-1} \ldots H_{t-p}$ are previous period values of the H series and μ_t is as previously defined. Equation [2] is an Autoregressive (AR) process of order p, and is usually denoted as AR (p).

3.4 The Autoregressive Moving Average (ARMA) model

An ARMA (p, q) process is just a mere combination of AR (p) and MA (q) processes. Thus, by combining equations [1] and [2]; an ARMA (p, q) process may be specified as shown below:

$$H_t = \sum_{i=1}^{p} \beta_i H_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \quad \ldots\ldots [3]$$

3.5 The Autoregressive Integrated Moving Average (ARIMA) model

A stochastic process H_t is referred to as an Autoregressive Integrated Moving Average (ARIMA) [p, d, q] process if it is integrated of order "d" [I (d)] and the "d" times differenced process has an ARMA (p, q) representation. If the sequence $\Delta^d H_t$ satisfies an ARMA (p, q) process; then the sequence of H_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d H_t = \sum_{i=1}^{p} \beta_i \Delta^d H_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \quad \ldots\ldots [4]$$

where Δ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$.

3.6 Data Collection

This study is based on annual observations (that is, from 1990 – 2018) on the number of new HIV infections in adults (ages 15 years and above) [denoted as H] in Rwanda. Out-of-sample forecasts will cover the period 2019 – 2030. All the data was gathered from the World Bank online database.

3.7 Diagnostic Tests & Model Evaluation

3.7.1 Stationarity Tests: Graphical Analysis

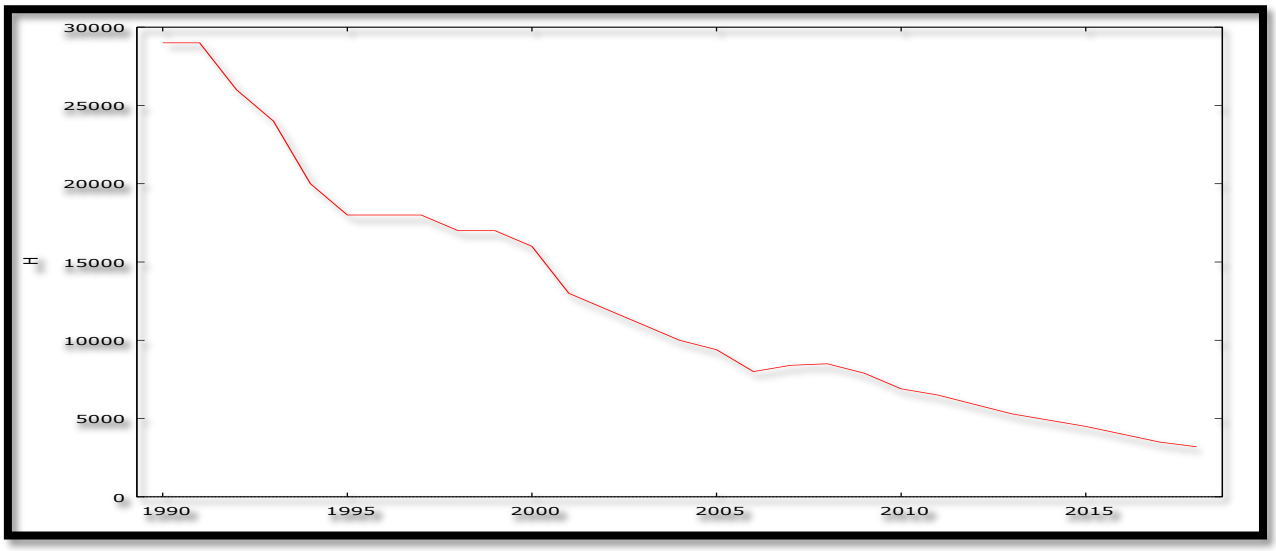

Figure 1

3.7.2 The Correlogram in Levels

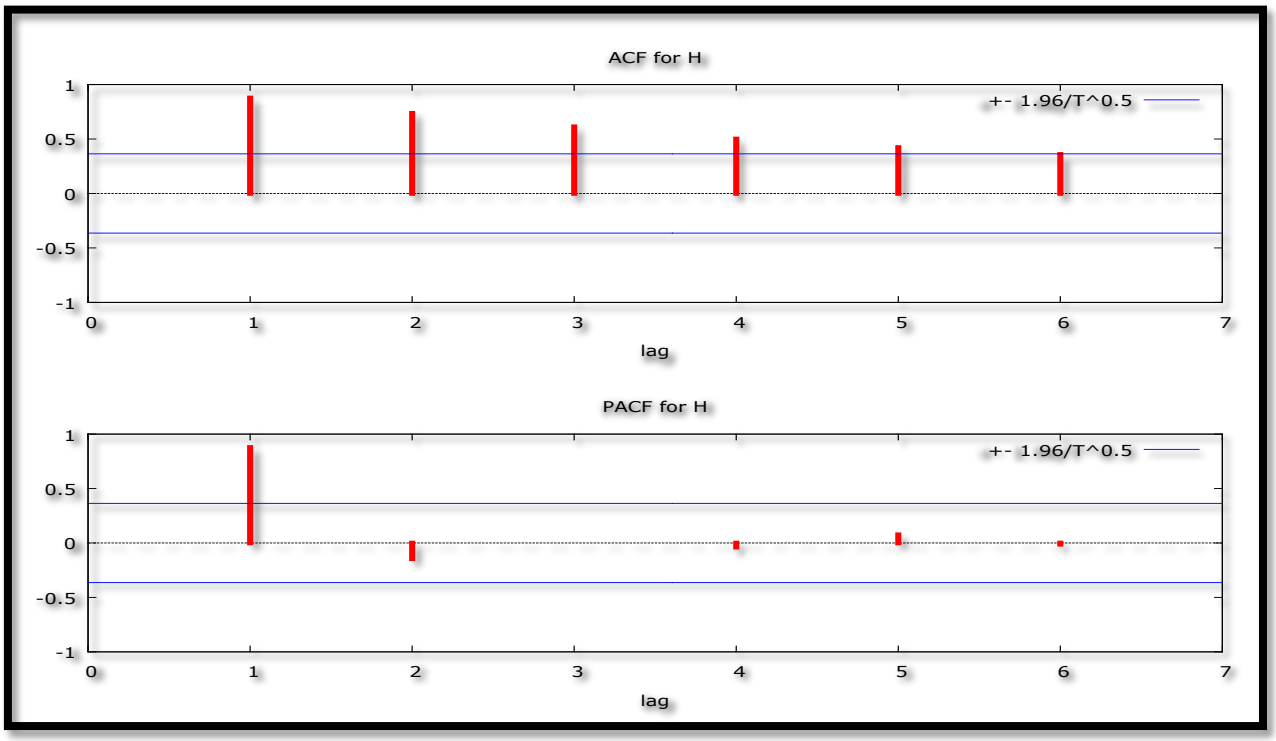

Figure 2: Correlogram in Levels

3.7.3 The ADF Test in Levels

Table 1: with intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
H	-2.998853	0.0472	-3.689194	@1%	Non-stationary
			-2.971853	@5%	Stationary
			-2.625121	@10%	Stationary

Table 1 shows that H is an I(0) variable; as suggested by figure 1.

3.7.4 Evaluation of ARIMA models (with a constant)

Table 2: Evaluation of ARIMA Models (with a constant)

Model	AIC	U	ME	RMSE	MAPE
ARIMA (1, 0, 5)	504.5987	0.90018	146.26	2895.2	8.6938
ARIMA (1, 0, 4)	502.9596	0.86015	209.55	2988.6	8.2455
ARIMA (1, 0, 3)	**502.2407**	0.82007	82.663	2885.7	8.2808
ARIMA (1, 0, 2)	503.6908	0.82811	-56.052	2756.2	8.4523
ARIMA (1, 0, 1)	503.8083	0.85714	-126.16	2797.3	8.5585
ARIMA (1, 0, 0)	511.6064	1.051	-452.11	2793.6	10.519
ARIMA (5, 0, 1)	506.1944	0.76803	183.25	2873.2	7.8686

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018b) Similarly, the U statistic can be used to find a better model in the sense that it must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018a). In this research paper, only the AIC is used to select the optimal model. Therefore, the ARIMA (1, 0, 3) model is finally chosen. This model, in other words, is exactly an ARMA (1, 3) process. However, for consistency reasons, we describe it as an ARIMA (1, 0, 3) model.

3.8 Residual & Stability Tests

3.8.1 Correlogram of the Residuals of the ARIMA (1, 0, 3) Model

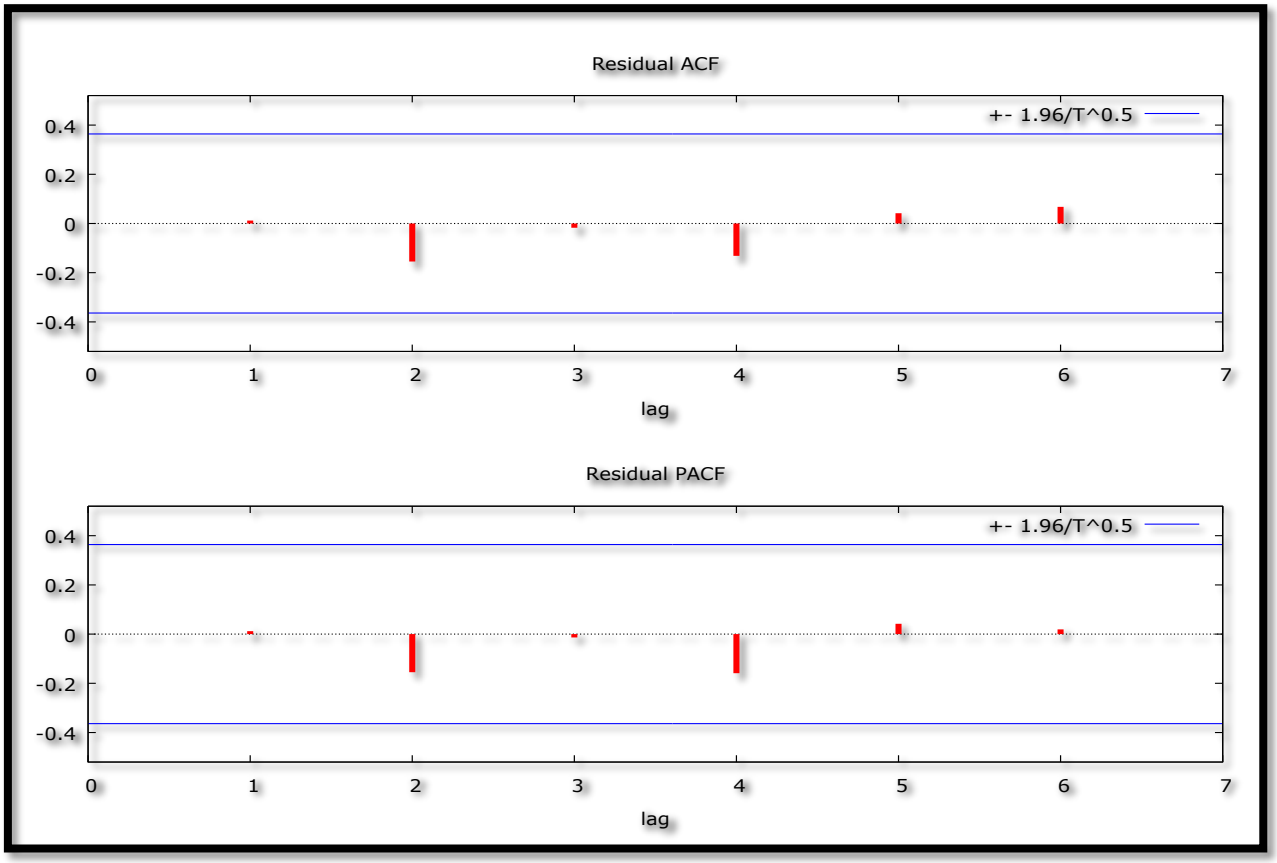

Figure 3: Correlogram of the Residuals

Figure 3 indicates that the estimated optimal ARIMA (1, 0, 3) model is adequate since ACF and PACF lags are quite short and within the bands. This implies that the "no autocorrelation" assumption is not violated in this paper: this also suggests that the selected model is stable.

4.0 FINDINGS OF THE STUDY

4.1 Results

Table 3: Main Results

ARIMA (1, 0, 3) Model:

Guided by equation [4], the chosen optimal model, the ARIMA (1, 0, 3) model can be expressed as follows:

$$H_t = 14463.7 + 0.974225H_{t-1} + 0.545770\mu_{t-1} + 0.402439\mu_{t-2} + 0.403937\mu_{t-3} \ldots\ldots\ldots\ldots [5]$$

Variable	Coefficient	Standard Error	z	p-value
constant	14463.7	1031.42	14.02	0.0000***
β_1	0.974225	0.0602336	16.17	0.0000***
α_1	0.545770	0.180436	3.025	0.0025***
α_2	0.402439	0.202675	1.986	0.0471**
α_3	0.403937	0.193696	2.085	0.0370**

Table 3 shows the main results of the ARIMA (1, 0, 3) model.

Forecast Graph

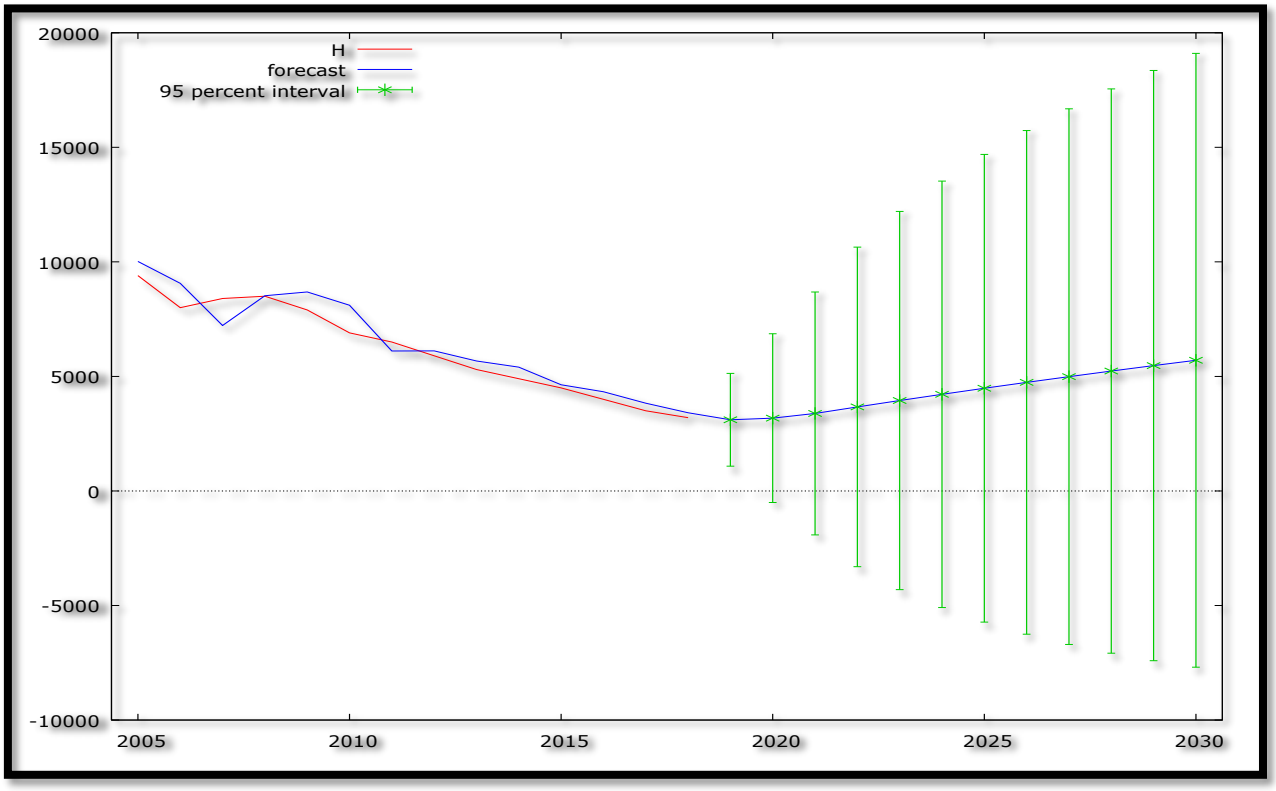

Figure 4: Forecast Graph – In & Out-of-Sample Forecasts

Figure 4 shows the in-and-out-of-sample forecasts of the H series. The out-of-sample forecasts cover the period 2019 – 2030.

Predicted H– Out-of-Sample Forecasts Only

Table 4: Predicted

Year	Prediction	Standard Error	95% Confidence Interval
2019	3106.65	1032.87	(1082.26, 5131.03)
2020	3179.12	1879.25	(-504.149, 6862.38)
2021	3383.46	2704.67	(-1917.59, 8684.52)
2022	3669.05	3558.33	(-3305.14, 10643.2)
2023	3947.28	4211.42	(-4306.95, 12201.5)
2024	4218.34	4748.92	(-5089.37, 13526.1)
2025	4482.41	5208.01	(-5725.10, 14689.9)
2026	4739.68	5609.09	(-6253.94, 15733.3)
2027	4990.31	5964.87	(-6700.61, 16681.2)
2028	5234.49	6283.94	(-7081.80, 17550.8)
2029	5472.37	6572.46	(-7409.41, 18354.1)
2030	5704.11	6835.04	(-7692.32, 19100.5)

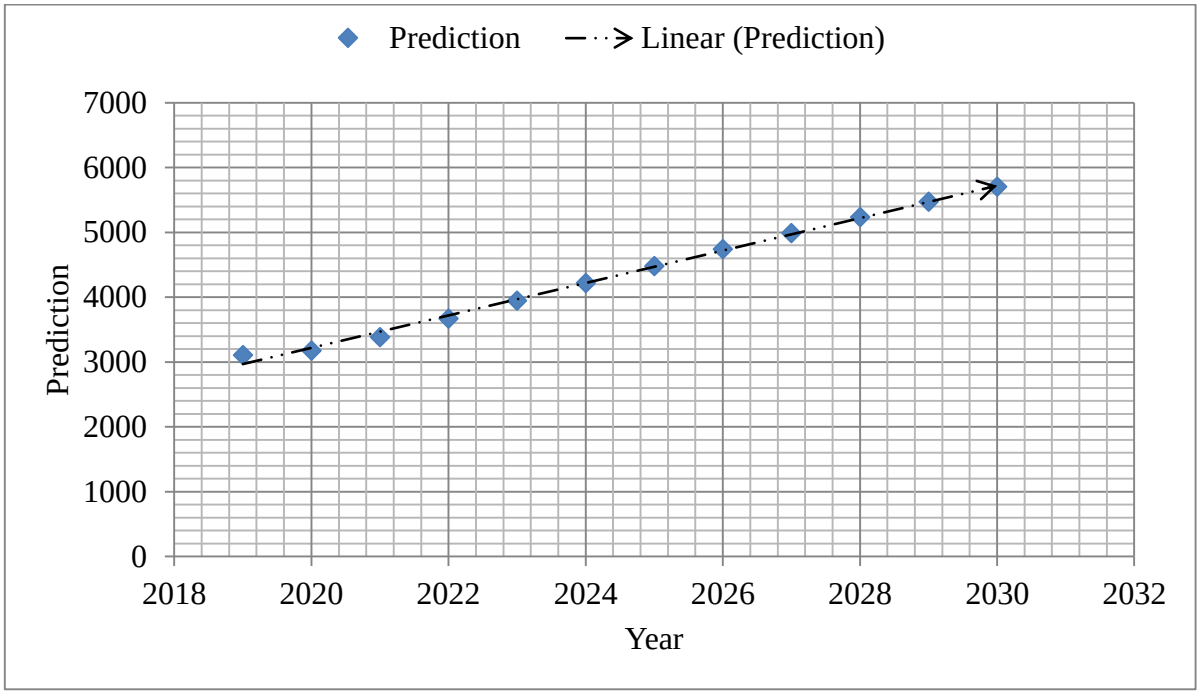

Figure 5: Graphical Analysis of Out-of-Sample Forecasts

Table 4 and figure 5 show the out-of-sample forecasts only. The number of new HIV infections in adults is projected to rise from 3107 in 2019 to almost 5704 by 2030. These findings are consistent with many previous studies such as Mwumvaneza et al. (2017) and Ingabire et al. (2019). The results of this study are not surprising given that knowledge of STIs and HIV/AIDS is still poor in Rwanda (Adedimeji et al., 2019).

5.0 CONCLUSION

The study shows that the ARIMA (1, 0, 3) model is a stable and suitable model to forecast the annual number of new HIV infections in adults in Rwanda over the period 2019 – 2030. The model predicts a marked increase in the annual number new HIV infections in the country. The study recommends that the government of Rwanda should continue scaling up HIV prevention and treatment access; with special emphasis on behavior change interventions, particularly increased condom use and encouraging people to stick to one faith sexual partner. The government of Rwanda should also engage in massive HIV/AIDS educational campaigns throughout the country. Public health policy makers in Rwanda ought to strengthen HIV, TB, and Sexual & Reproductive Health programme linkages around the country. Rwanda, being one of the low-circumcision countries in Africa, there is need for up scaling of medical male circumcision as an additional HIV prevention strategy.

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