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MODELING AND PROJECTION OF NEW HIV INFECTIONS IN CHILDREN AGED BETWEEN 0 AND 14 YEARS IN ZIMBABWE USING BOX-JENKINS ARIMA MODELS

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ABSTRACT

This paper uses annual time series data on new HIV infections in children aged between 0 – 14 in Zimbabwe from 1990 – 2018; to forecast new HIV infections over the period 2019 – 2023. The study applies the generalized Box-Jenkins ARIMA technique. Diagnostic tests show that C is an I (2) series. Model evaluation criteria indicate that the optimal model is the ARIMA (1, 2, 0) model. The study concludes that it is possible to have an AIDS-free generation in Zimbabwe as hinted by a projected sharp downwards trend of new HIV infections in the out-of-sample period. The study offers a 4-fold policy prescription in order to prevent and control new HIV infections in children in the country.

1.0 INTRODUCTION

The HIV/AIDS epidemic has become a serious health and development problem (Takarinda *et al.*, 2016) in many countries around the world and is a major contributing factor to childhood disease and mortality (UNAIDS, 2002). HIV (Human Immunodeficiency Virus) is the virus that causes AIDS (Acquired Immune Deficiency Syndrome). HIV destroys the biological ability of the human body to fight off opportunistic infections. A person can be infected with HIV for a long time without showing any symptoms of the disease. Nonetheless, during that period before a person develops symptoms, he or she can transmit the infection through sexual contact to other, uninfected people. An infected woman can also transmit the disease to her unborn child or breast-feeding infant. AIDS itself is defined in terms of how much deterioration of the immune system has taken place as seen by the presence of opportunistic infections (Ministry of Health & Child Welfare, 1998).

The first AIDS case was reported in Zimbabwe in 1985 (Mapenzauswa, 2004). Since then more patients began to present with illnesses suggestive of HIV infection. Young adults presented with severe respiratory infections, herpes zosters, persistent generalized lymphadenopathy and diarrhea associated with weight loss (Topley, 1988; Dehne *et al.*, 1992). Children were seen who seemed to be suffering from malnutrition but whose socio-economic backgrounds were inconsistent with poverty (Ikeogu *et al.*, 1997; Ticklay *et al.*, 1997). Unfortunately such patients failed to respond to standard nutritional and conventional medical treatments, suggesting an immunodeficiency condition (Duri *et al.*, 2013).

Children may acquire HIV infection during pregnancy, labour, delivery or after birth during breast feeding. Fortunately, most children born to HIV infected mothers are not infected. Estimates of the rates of mother-to-child transmission (MTCT) of HIV have ranged (without the use of antiretroviral (ARV) drugs

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during pregnancy and in the newborn) from 15-25% in industrialized countries to 25-35% in developing countries. Among infected infants who are not breast-fed, about two-thirds of cases of MTCT occur around the time of delivery and the rest during pregnancy (mostly during the last two months). In societies where breast feeding is the norm, it accounts for about one-third of all transmissions. As a result, the proportion of infants infected through MTCT is higher in these societies than those where mothers with HIV infection can safely avoid breastfeeding. MTCT of HIV is a huge problem in Zimbabwe which has become the major cause of infant and child mortality (Mahomva, 2007). It is the most significant (90%) source of HIV infection in children below the age of 15 years (Duri *et al*., 2013). HIV infection can also be transmitted through blood transfusion and the use of contaminated needles and syringes, especially in emergency situations. Child sexual abuse is another significant cause of childhood HIV infection, especially in developing countries where discussions about child sexual abuse is still a taboo. It is important to know that, with good care and support, infected children can live a longer and better life (UNAIDS, 2002).

Worthy to note is the fact that in Zimbabwe, all HIV positive patients are commenced on ART (antiretroviral therapy) regardless of WHO clinical staging. The ARV drugs dosages depend on age and weight of the patient. However, all HIV positive patients should be screened for TB before ART initiation, in line with government policy on HIV/TB program collaboration. In Zimbabwe, early detection and diagnosis of HIV in infants is done using DNA-PCR testing. Early ART initiation for HIV positive infants is critical to reduce morbidity and mortality in this age group. This study, whose 3-fold objectives are outlined below, will model and project new HIV infections in children aged between 0 and 14 years in Zimbabwe using ARIMA models. Literature is plenary with HIV related studies in Zimbabwe, for example, Topley (1988); Ikeogu *et al.* (1997); Ticklay *et al.* (1997); Mahomva (2007); Dube *et al.* (2008); Duri *et al.* (2013); Takarinda *et al.* (2016) and Nyoni & Nyoni (2020). With the exception of Nyoni & Nyoni (2020), so far, no Zimbabwean study has projected new HIV infections. This paper will be the second empirical paper in the country to project new HIV infections but will be different from Nyoni & Nyoni (2020) in the sense that the current endeavor focuses on analyzing new HIV infections in children aged between 0 and 14 yearly only. There is no doubt; this paper is the first country-specific study to investigate pediatric HIV in Zimbabwe from a time series forecasting perspective.

1.2 OBJECTIVES OF THE STUDY

i. To investigate the years during which new HIV infections in children peaked in Zimbabwe.
ii. To forecast the number of new HIV infections in children for the out-of sample period.
iii. To examine the pattern of new HIV infections in children for the out-of-sample period.

1.3 RELEVANCE OF THE STUDY

Globally, about 2.7 million children are currently living with HIV infection. In fact, more than 1500 children become infected with HIV every day. The vast majority (more than 90%) acquire the infection from their mother (UNAIDS, 2002). Eastern and Southern Africa is home to more than 60% of children and adolescents living with HIV (UNICEF, 2018). Zimbabwe has an estimated 1.3 million people living with HIV (Global AIDS Response Report, 2018) and is one of the Southern Sub-Saharan African countries that has been hardest hit by the pandemic (Ministry of Health and Child Care, 2014). Between 1980 and 2005, among 10 million children born in Zimbabwe, a cumulative 504000 were vertically infected with HIV (Dube *et al*., 2008). As of 2010, it is estimated that approximately 120000 children between the ages of 0 – 14 are living with HIV/AIDS of which 3.4% of children aged 10 years are long-term survivors following MTCT (Ferrand *et al*., 2009). As of 2018, only 4800 children between the ages of 0 – 14 are living with HIV/AIDS as shown in figure 1 below. Indeed, the numbers have declined. This study, whose objectives are stated above, will go a long way in helping policy makers in the country in terms of providing information on designing appropriate controlling and preventive measures in order to bring a long term solution.

2.0 LITERATURE REVIEW

In Asia, Yu *et al.* (2013) employed the ARIMA model to forecast the number of new HIV infections in the Korean population using a data set covering the period 1985 to 2012. The results of the study basically indicate that the ARIMA (2, 2, 1) model is the optimal model. Using an annual data set covering the period 1990 to 2013, Demissew (2015); evaluated ARIMA models in order to establish the trend and project HIV/AIDS epidemics in Ethiopia. The ARIMA (2, 3, 2) model appeared to be providing the best fit for the

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observed data set. The prediction showed that the prevalence of HIV/AIDS would decrease in Ethiopia for the next 5 years. In Uganda, Rubaihayo *et al.* (2016) relied upon monthly observational data collected over a 10-year period (2004-2013) by The AIDS Support Organization (TASO) to forecast 5-years annual prevalence of any OI covering the period 2014 – 2018. The OIs considered include 14 AIDS-defining OIs, 2 non-AIDS defining OIs (malaria & geohelminths) and HIV associated Kaposi's sarcoma. The Box-Jenkins methodology was used. The results indicate that the ARIMA (1, 1, 1) model was the most parsimonious model and best fit model for the data.

In Nigeria, Abu & Emeje (2019); using an annual data set covering the period 1991-2015, examined ARIMA models in order to establish the prevalence of HIV. Model performance tests based on the MAE and the MSE showed that the ARIMA (7, 1, 0) model was the optimal model. The forecast results showed that there would be 1.5%, 0.97% and 0.71% prevalence in 2016, 2017 and 2018, respectively. In a Zimbabwean study, Nyoni & Nyoni (2020) used monthly time series data on new HIV infections at Silobela District Hospital (SDH) from January 2014 to December 2018; to predict new HIV infections based on the Box-Jenkins technique. The study actually presented the SARIMA $(0, 1, 1)(0, 1, 1)_{12}$ model, which indicated that new HIV infections in the community of Silobela will decline over the out-of-sample period.

3.0 MATERIALS & METHODS

ARIMA Models

The Box-Jenkins ARIMA model continues to be used in modeling and forecasting new HIV infections (Yu *et al.*, 2013, Demissew, 2015; Rubaihayo *et al.*, 2016; Abu & Emeje, 2019; Nyoni & Nyoni, 2020). ARIMA models are used for observable non-stationary processes that have some clearly identifiable trends (Kuhe *et al.*, 2016). This study will employ the ARIMA models in order to analyze annual new HIV infections in children in Zimbabwe. ARIMA models are accredited to Box & Jenkins (1970), hence the term "Box-Jenkins ARIMA models". The general ARIMA (p, d, q) model can be represented by a backward shift operator as follows:

$$\emptyset(B)(1-B)^d C_t = \theta(B)\mu_t \quad \ldots [1]$$

Where the autoregressive (AR) and moving average (MA) characteristic operators are:

$$\emptyset(B) = \left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p\right) \quad \ldots [2]$$

$$\theta(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q\right) \quad \ldots [3]$$

and

$$(1-B)^d C_t = \Delta^d C_t \quad \ldots [4]$$

Where $\emptyset$ is the parameter estimate of the autoregressive component, θ is the parameter estimate of the moving average component, Δ is the difference operator, d is the difference, B is the backshift operator and μ_t is the disturbance term.

The Box – Jenkins 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).

Data Collection

This study is based on 29 observations of annual total new HIV infections in children aged between 0 and 14 years (C) in Zimbabwe. All the data was gathered from the World Bank online database.

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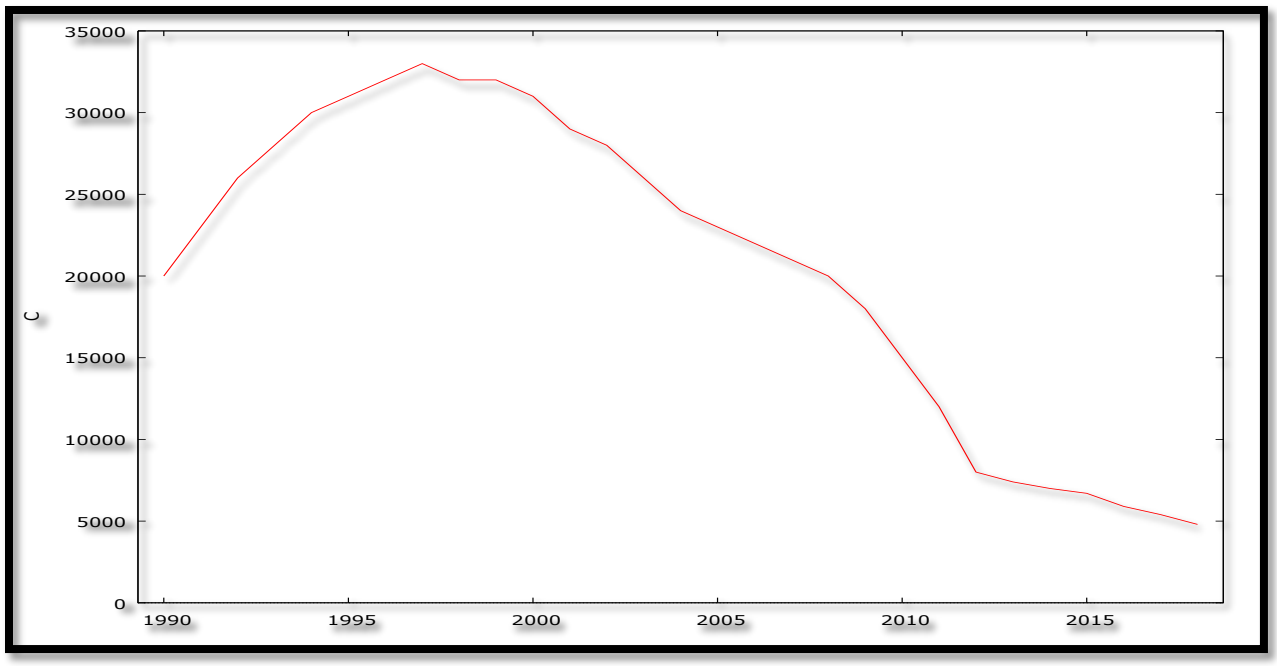
Diagnostic Tests & Model Evaluation
Stationarity Tests: Graphical Analysis

Figure 1



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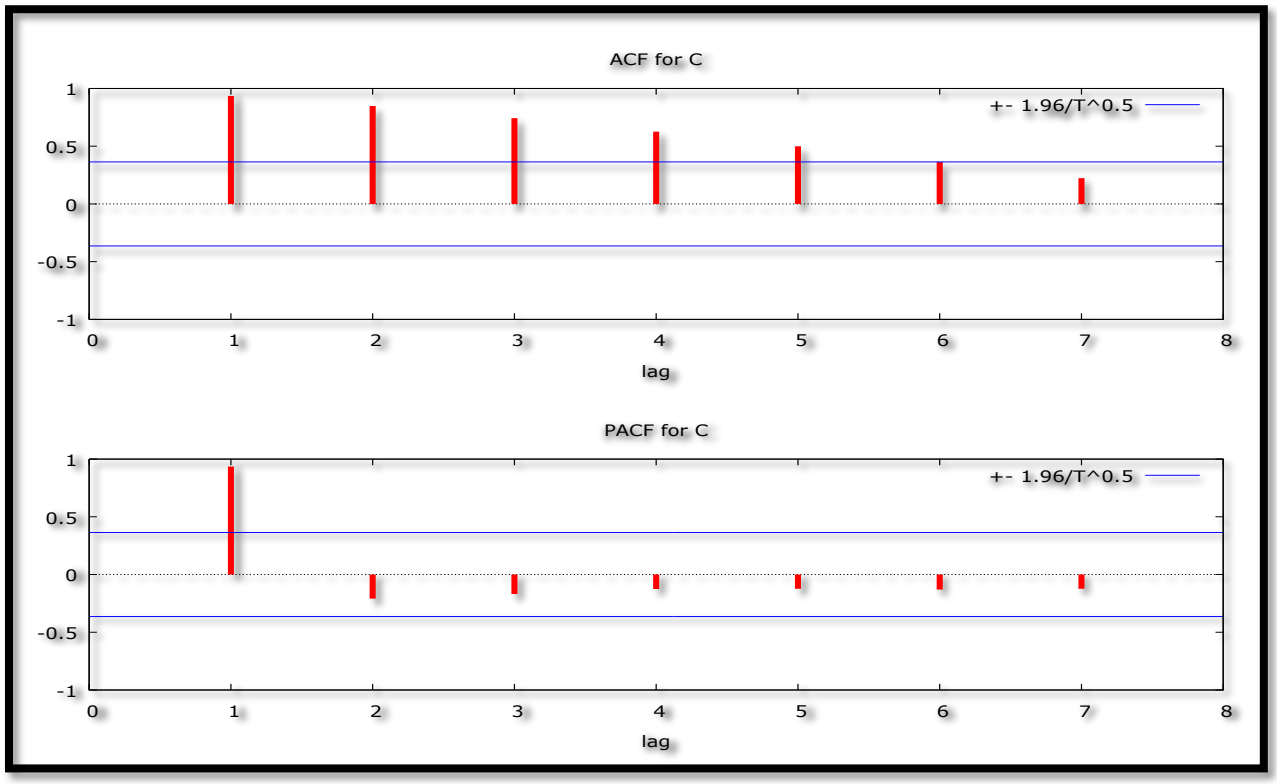
The Correlogram in Levels

Figure 2



The Augmented-Dickey-Fuller (ADF) Test

Table 1: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
C	-0.755823	0.8155	-3.699871	@1%	Not stationary
			-2.976263	@5%	Not stationary
			-2.627240	@10%	Not stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
C	-3.040789	0.1402	-4.339330	@1%	Not stationary
			-3.587527	@5%	Not stationary
			-3.229230	@10%	Not stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
C	-1.626061	0.0969	-2.653401	@1%	Not stationary
			-1.953858	@5%	Not stationary
			-1.609571	@10%	Stationary

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The Correlogram (at 1st Differences)

Figure 3

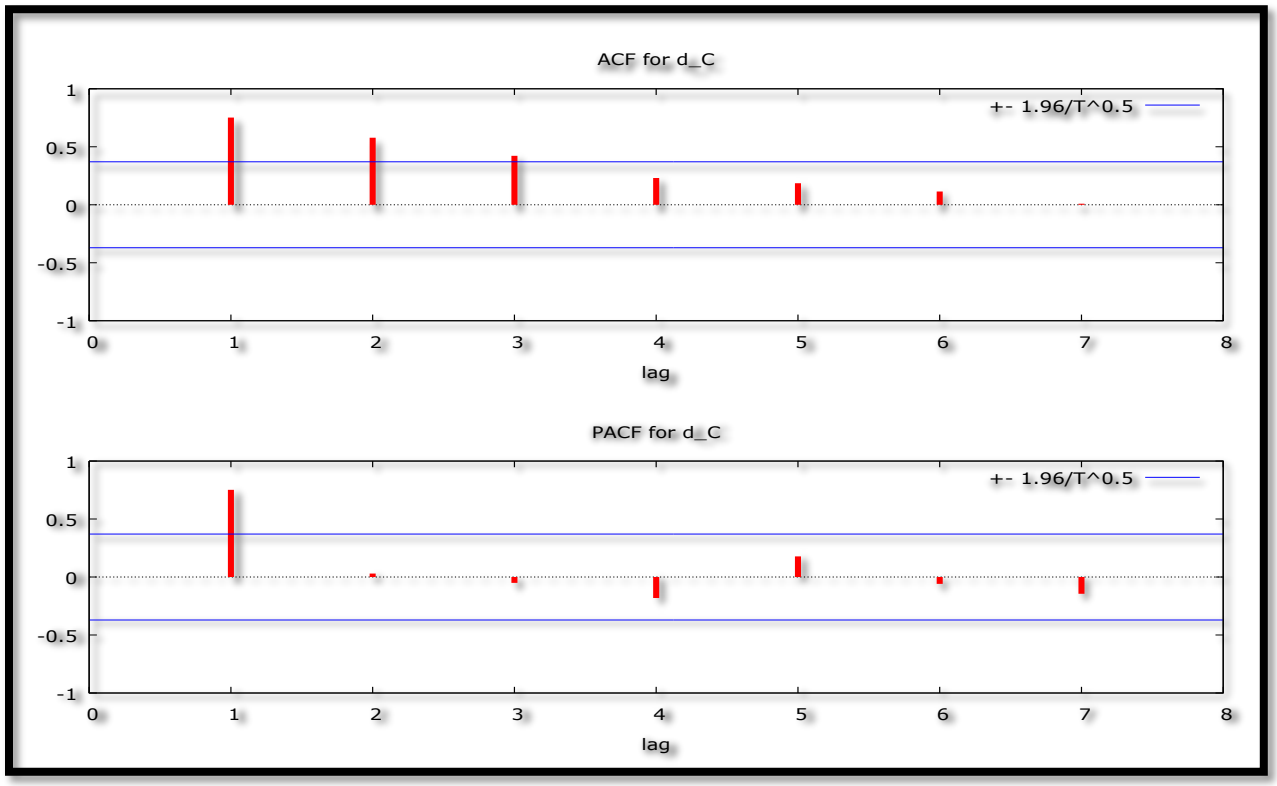

Table 4: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(C)	-2.382047	0.1559	-3.699871	@1%	Not stationary
			-2.976263	@5%	Not stationary
			-2.627420	@10%	Not stationary

Table 5: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(C)	-2.000219	0.5750	-4.339330	@1%	Not stationary
			-3.587527	@5%	Not stationary
			-3.229230	@10%	Not stationary

Table 6: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(C)	-2.008454	0.0445	-2.653401	@1%	Not stationary
			-1.953858	@5%	Stationary
			-1.609571	@10%	Stationary

Figure 1 shows the trend of C over the period 1990 – 2018. New HIV infections in children aged between 0 and 14 were on the rise between 1990 and 1997. This could be attributed to the fact that the pandemic was not yet well known and properly prevented in developing countries such as Zimbabwe. Since the onset of the new millennium in 2000, new HIV infections in children have followed a downwards trajectory. This could be attributed to the government response to the pandemic, especially through implementing various preventive measures. Figures above, that is; 2 and 3 and tables above, that is; 1 to 6 also show that C is not stationary in levels and even after taking first differences.

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The Correlogram in (2nd Differences)

Figure 4

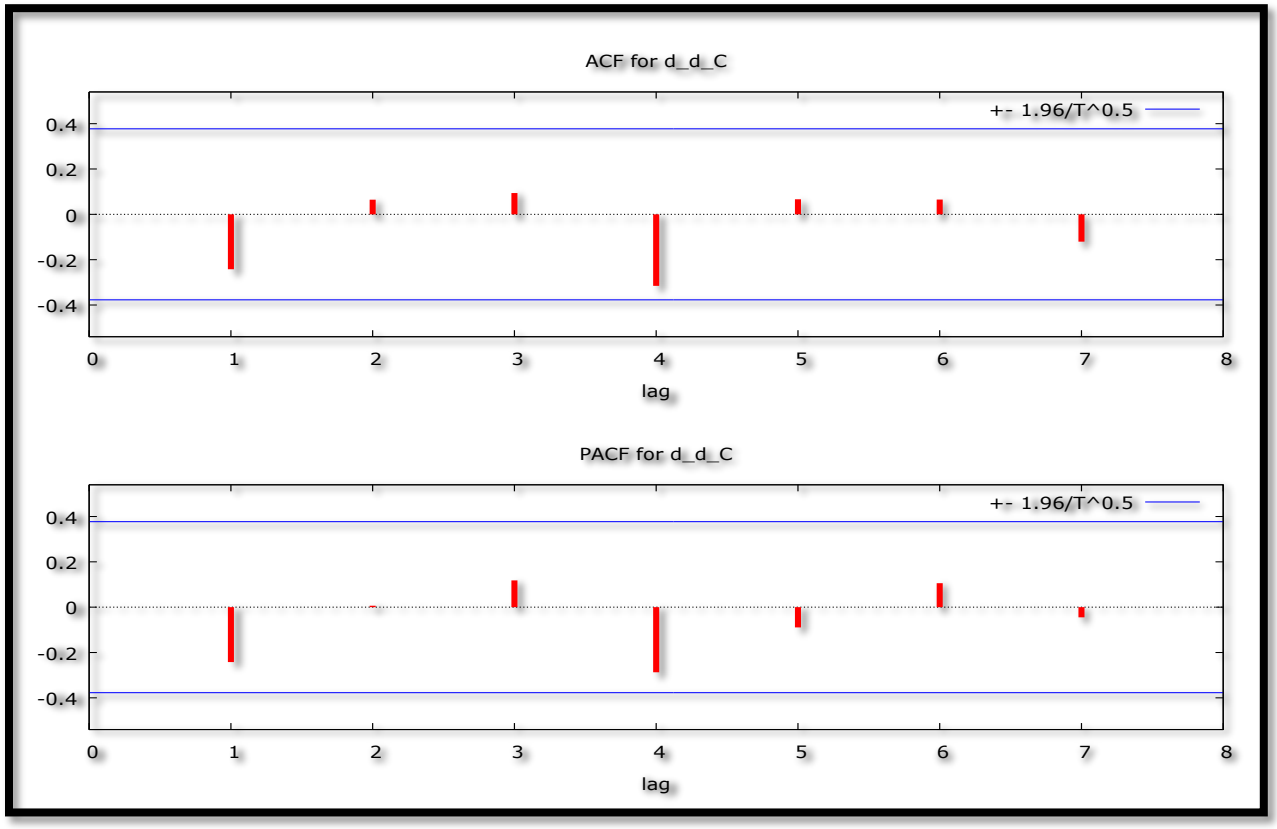

Table 7: 2nd Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(D(C))	-6.274801	0.0000	-3.711457	@1%	Stationary
			-2.981038	@5%	Stationary
			-2.629906	@10%	Stationary

Table 8: 2nd Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(D(C))	-6.745379	0.0000	-4.356068	@1%	Stationary
			-3.595026	@5%	Stationary
			-3.233456	@10%	Stationary

Table 9: 2nd Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(D(C))	-6.252229	0.0000	-2.656915	@1%	Stationary
			-1.954414	@5%	Stationary
			-1.609329	@10%	Stationary

Figure 4 and tables 7 – 9 illustrate that the series under consideration is I (2).

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Evaluation of ARIMA models (without a constant)

Table 10: Evaluation of ARIMA Models

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 2, 1)	454.2985	0.87067	-158.86	679.42	974.6	4.9218
ARIMA (1, 2, 0)	**452.3098**	0.87084	-160.84	680.93	974.81	4.9524
ARIMA (0, 2, 1)	452.4601	0.86897	-163.77	687.39	977.73	5.0038
ARIMA (2, 2, 1)	456.2503	0.87576	-151.17	674.91	973.7	4.87
ARIMA (3, 2, 1)	457.1566	0.93523	-137.99	667.9	952.87	5.3766
ARIMA (1, 2, 3)	457.5227	0.93377	-124.68	661.76	959.82	5.1923
ARIMA (0, 2, 3)	455.9345	0.88688	-142.48	695.94	966.96	5.2782
ARIMA (3, 2, 0)	455.8078	0.92018	-136.24	666.12	965.21	5.0724
ARIMA (2, 2, 0)	454.2829	0.87127	-155.55	676.74	974.31	4.8777
ARIMA (0, 2, 2)	454.0088	0.89918	-133.49	683.1	968.93	5.1521

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 paper, only the AIC is used to select the parsimonious model. Therefore, the ARIMA (1, 2, 0) model is chosen.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (1, 2, 0) Model

Table 11: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R	-4.944338	0.0005	-3.724070	@1%	Stationary
			-2.986225	@5%	Stationary
			-2.632604	@10%	Stationary

Table 12: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R	-5.295612	0.0013	-4.374307	@1%	Stationary
			-3.603202	@5%	Stationary
			-3.238054	@10%	Stationary

Table 13: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R	-4.962135	0.0000	-2.660720	@1%	Stationary
			-1.955020	@5%	Stationary
			-1.609070	@10%	Stationary

Tables 11 – 13 indicate that the residuals of the chosen optimal model, the ARIMA (1, 2, 0) model; are stationary. This indicates that the applied model is stable. This has also been confirmed in figure 6 below. Hence the selected optimal model is suitable for forecasting new HIV infections in children aged between 0 and 14 in Zimbabwe.

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Correlogram of the Residuals of the ARIMA (1, 2, 0) Model

Figure 5: Correlogram of the Residuals

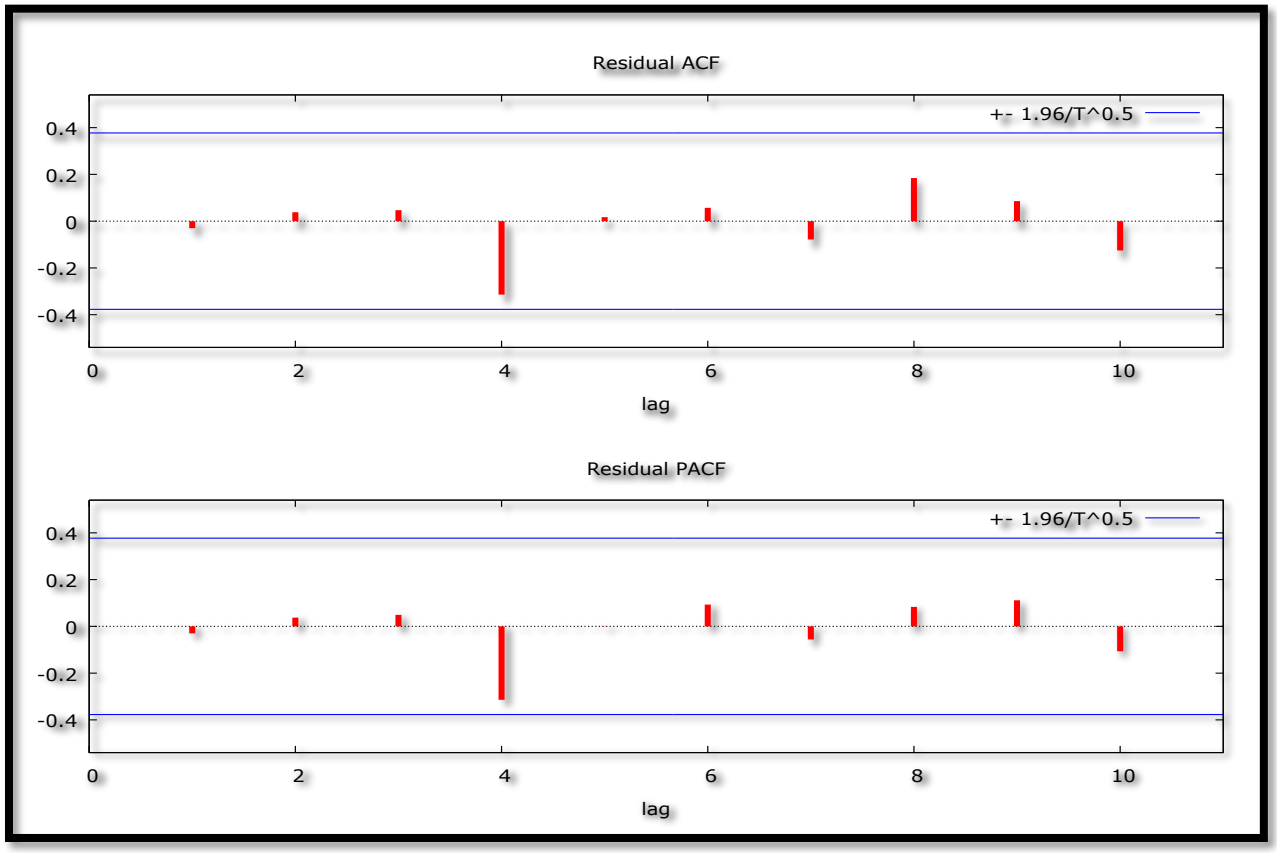

Figure 5 indicates that the estimated ARIMA (1, 2, 0) model is adequate since ACF and PACF lags are quite short and within the bands. This implies that the assumption of no autocorrelation is valid in this study.

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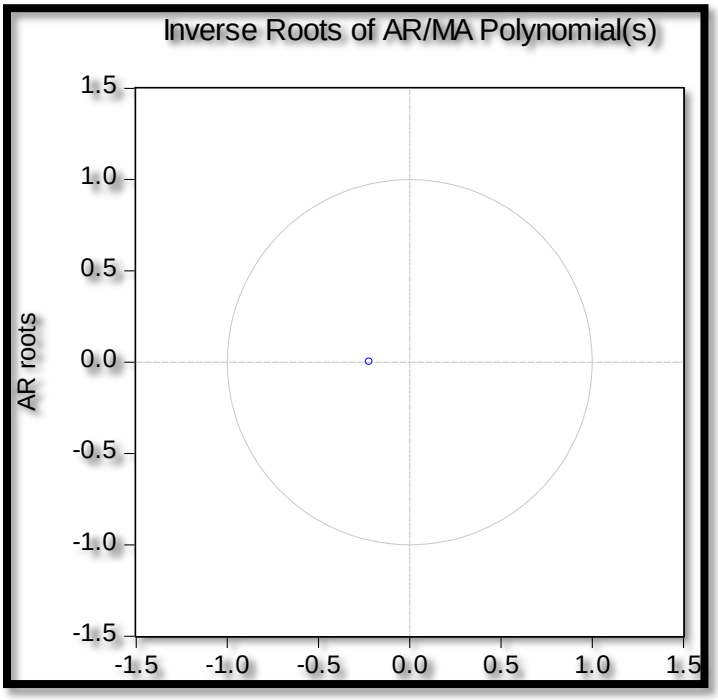
Stability Test of the ARIMA (1, 2, 0) Model

Figure 6: Inverse Roots



Since all the AR roots lie inside the unit circle, it means that the estimated ARIMA process is (covariance) stationary; thus confirming that the ARIMA (1, 2, 0) model is quite stable and suitable for forecasting new HIV infections in children (0-14 years old) in Zimbabwe.

4.0 FINDINGS

Descriptive Statistics

Table 14: Descriptive Statistics

Description	Statistic
Mean	20731
Median	23000
Minimum	4800
Maximum	33000
Standard deviation	9695.7
Skewness	-0.42985
Excess kurtosis	-1.2429

As shown above, the mean is positive, i.e. 20731. This means that the average number of new HIV infections over the study period is 20731 infections per annum. The minimum number of new HIV infections over the study period is 4800 infections and this was recorded in 2018 while the maximum number of infections is 33000 and this was recorded in 1997. The skewness is -0.42985 and the most essential characteristic is that it is negative, meaning that C is negatively skewed and non-symmetric. Excess kurtosis is -1.2429; showing that C series is not normally distributed.

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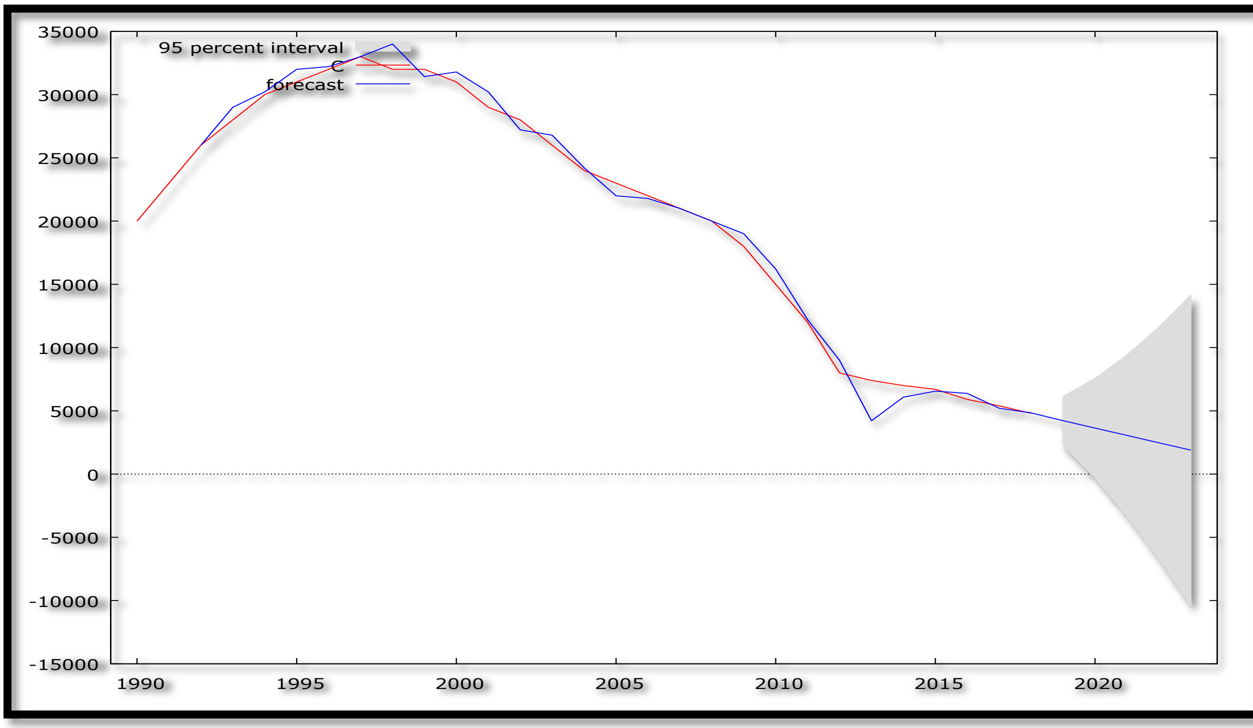
Results Presentation

Table 15: Main Results

ARIMA (1, 2, 0) Model:				
$\Delta^2 C_{t-1} = 1.3784\Delta^2 C_{t-1}$ …………………………………………………………………[5]				
Variable	**Coefficient**	**Standard Error**	**z**	**p-value**
ϕ_1	-0.212202	0.187776	-1.130	0.2584

Forecast Graph

Figure 7: Forecast Graph – In & Out-of-Sample Forecasts



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Predicted C

Figure 8: Graphical Analysis of Out-of-Sample Forecasts

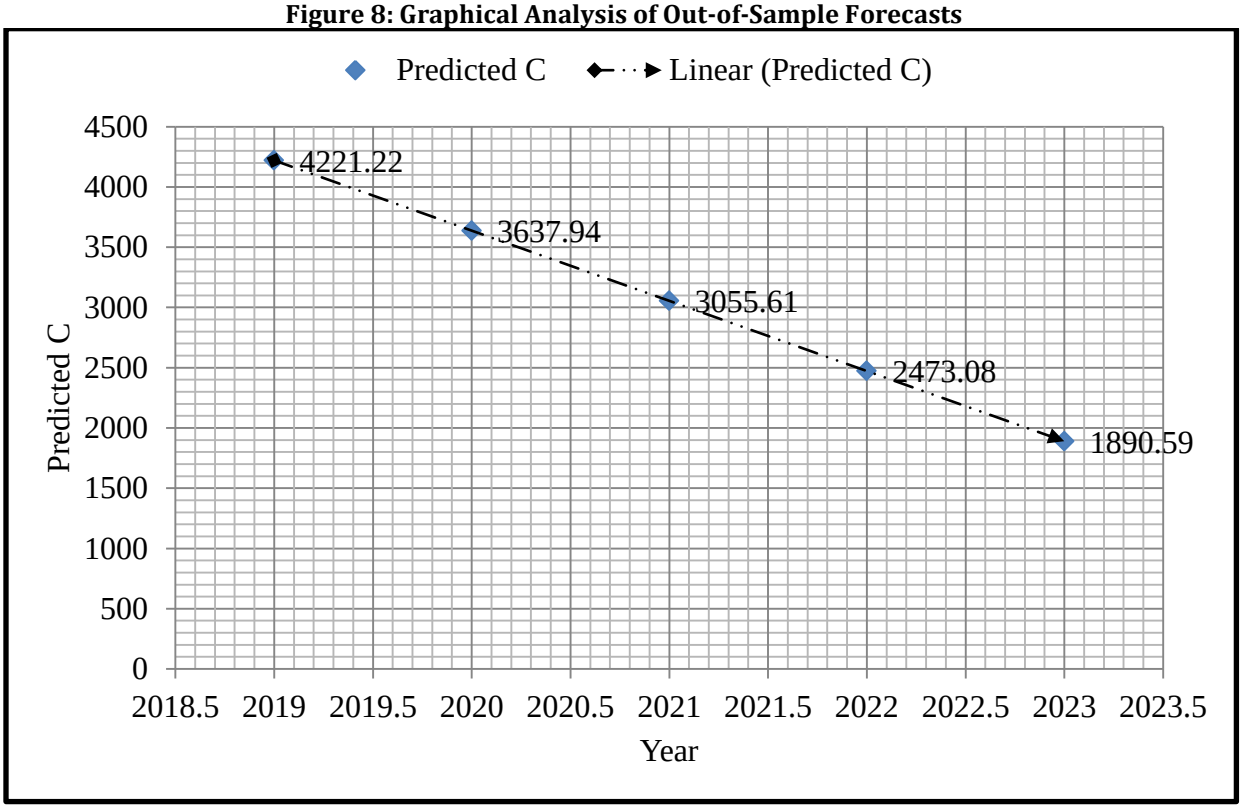

Table 15 shows the main results of the ARIMA (1, 2, 0) model. Figure 7 and 8 are out-of-sample forecasts of the ARIMA (1, 2, 0) model. Years ago, as noted by UNICEF (2009), when the devastating impact of the AIDS pandemic on children was just becoming apparent, there was no way to imagine an AIDS-free generation in the foreseeable future. Fortunately, the results of this study show that it is possible to have an AIDS-free generation in Zimbabwe. As shown in figure 8, the annual number of new HIV infections in children aged 0 to 14, over the out-of-sample period, show a sharply downwards trend. This means that new HIV infections in children (0-14 years old) are expected to drop significantly in the near future. This is quite reasonable and already anticipated, for a developing country like Zimbabwe, where the implementation of HIV-related programs has been consistent over the years. These results are not surprising, but rather consistent with Nyoni & Nyoni (2020). The results of the study are also consistent with Abu & Emeje (2019) who did a similar study in Nigeria. The results of the study are also in line with the estimates done by the Ministry of Health and Child Care (2018), which provides evidence of a decline in new HIV infections in children. The results of this study also tally with the observation made by Duri *et al.* (2013) that Zimbabwe is one of the few countries in the world currently experiencing a general decline in HIV prevalence.

Policy Prescription

i. Prevent HIV infection in parents-to-be. This is arguably the most effective way to reduce the number of children who become infected with HIV. The following strategies can be used:
   - ✓ Correct and consistent condom use.
   - ✓ Voluntary Medical Male Circumcision (VMMC).
   - ✓ Sexual behaviour change.

ii. Prevent unplanned pregnancies in HIV-infected women.

iii. Among HIV positive pregnant women, antiretroviral prevention treatment, safe delivery practices and safe infant-feeding options to minimize the risk of MTCT of HIV

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should be provided. Hence, the intensification of the PMTCT interventions in the country.

iv. Offering antiretroviral therapy within 72 hours to victims of rape (sexual abuse).

5.0 CONCLUSION

It is possible to materialize an AIDS-free generation in Zimbabwe, despite the fact that HIV/AIDS remains one of the lethal diseases which cause millions of deaths around the globe. It is encouraging to note that much continues to be done on the containing of HIV/AIDS in different parts of Zimbabwe even though the epidemic remains one of the onerous health problems threating the health system of the country. From this study, the ARIMA (1, 2, 0) model appeared to be the optimal model for analyzing new HIV infections in children (0 – 14 years old) in Zimbabwe. The out-of-sample forecasts show that new HIV infections in children in Zimbabwe will decline over the next 5 years, to as low as 1891 in 2023; especially if control and preventive measures continue to be put in place effectively. Further research may look into applying the ARIMAX model to analyze new HIV infections in children in Zimbabwe. This can potentially uncover interesting results due to the fact that the ARIMAX model is a multivariate version of the ARIMA model and is capable of capturing the impact of other epidemiological factors on new HIV dynamics in children.

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