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Modelling International Tourist Arrivals Volatility in Zimbabwe Using a GARCH Process

Tendi Makoni*
Department of Mathematical Statistics and Actuarial Science, University of the Free State, South Africa, Email, tpmakoni@gmail.com

Delson Chikobvu
Department of Mathematical Statistics and Actuarial Science, University of the Free State, South Africa

Corresponding Author

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Abstract

The aim of the paper was to develop bootstrap prediction intervals for international tourism demand and volatility in Zimbabwe after modelling with an ARMA-GARCH process. ARMA-GARCH models have better forecasting power and are capable of capturing and quantifying volatility. Bootstrap prediction intervals can account for future uncertainty that arises through parameter estimation. The monthly international tourism data obtained from the Zimbabwe Tourism Authority (ZTA) (January 2000 to June 2017) is neither seasonal nor stationary and is made stationery by taking a logarithm transformation. An ARMA(1,1) model fits well to the data; with forecasts indicating a slow increase in international tourist arrivals (outside of the Covid-19 period). The GARCH(1,1) process indicated that unexpected tourism shocks will significantly impact the Zimbabwe international tourist arrivals for longer durations. Volatility bootstrap prediction intervals indicated minimal future uncertainty in international tourist arrivals. For the Zimbabwe tourism industry to remain relevant, new tourism products and attraction centres need to be developed, as well as embarking on effective marketing strategies to lure even more tourists from abroad. This will go a long way in increasing the much-needed foreign currency earnings needed to revive the Zimbabwean economy.

Keywords: ARMA, GARCH model, volatility, bootstrap, prediction interval

Introduction

Outside of the Covid-19 pandemic period, the tourism sector was growing continuously and was among the fastest-growing sectors around the world (United Nations World Tourism Organisation (UNWTO), 2016). The sector was now recognised as a source of foreign currency revenue by various countries including Zimbabwe. The tourism sector is identified as a key to poverty alleviation and economic growth in African countries (World Bank, 2006; Mitchell & Ashley, 2006). Considering that Zimbabwe is gifted with a lot of natural resources, minerals and natural wonders, making it enjoy a fair share of tourist arrivals from around the world. The tourism sector is now considered to be among vital pillars in reviving the economy in Zimbabwe. Zimbabwe has a vast array of tourism attractions and receives visitors from across the continent. About 80.7% of visitors come from Africa (mainly from Southern and Central Africa), 9.8% are from Europe, 5.7% are from the Americas, and 4% are from Asia and Oceania (Zimbabwe-Visitor Exit Survey Report, 2015/16). Tourists from these source markets bring in foreign currency that is needed by many industries in the country. Acquiring raw materials from outside the country needs foreign currency. The more tourist arrivals, the more are the foreign currency earnings.

The Zimbabwean tourism sector increased rapidly after the country's independence in 1980, with a 17.5% growth rate in arrivals and 18% annual increase in tourism receipts between the years 1989 and 1999 (Zimbabwe Tourism Trends & Statistics Report, 2000). Tourist arrivals and receipts dropped by 11% and 38% respectively between the years 1999-2000 due to the unusual political, social and economic environment (Zimbabwe Tourism Trends & Statistics Report, 2000). A decline in tourist arrivals and receipts impact negatively on the economy. Production declined and unemployment rose creating further problems and a vicious cycle. Zimbabwe recorded an annual decrease (8%) in tourist arrivals in 2002, an increase of 11% in 2003, 18% reduction in 2004, 16% reduction in 2005, an increase of 47% in 2006, increased by 10% in 2007, a 22% decline in 2008, a 3% increase in 2009, a growth of 11% in 2010, 10.3% decrease in 2011, 26% decline in 2012, 2% increase in 2013, an increase of 3% in 2014, an increase of 9% in 2015, an increase by 5% in 2016 and a further increase was expected in the year 2017 (Zimbabwe Tourism Trends & Statistics Annual Report, 2002-2016). The figures show volatility in tourist arrivals. An increase in tourist arrivals result in an increase in foreign currency earnings, tourism receipts, hence an improvement in the economy.

Variations in tourist arrival figures resemble a stochastic process that need to be modelled and understood since it impacts planning (transport, accommodation, among others) in the country. Tourism products are perishable; hence, the prediction of accurate future tourist arrivals becomes critical to the government and tourism management authorities. According to Louw and Saayman (2013), missed opportunities arise when tourism service providers do not have an idea about future tourist arrivals. Investment opportunities need not be missed. International tourism receipts boost the country's foreign currency reserves and the tourism sector is contributing immensely to the country's Gross Domestic Product (GDP). The country's imports and exports are linked to the tourism industry. Most investment opportunities in the country are interconnected to the tourism sector and it cannot be disputed that the tourism sector is a tool for employment creation and poverty eradication in Zimbabwe and Africa at large. Zimbabwe suffered continued economic uncertainty due to declining productivity on resettled farms and shortages of foreign exchange (African Development Bank (AfDB)/Organisation for Economic Co-operation and Development (OECD) (AfDB/OECD), 2004). There are limited rail services, foreign currency shortages and shortages of fuel in the country and all are creating a vicious cycle. Due to foreign currency scarcity, the National Railways of Zimbabwe (NRZ), Wankie Colliery and Zimbabwe Electricity Supply Authority (ZESA) are not fully functional. Maintenance parts need to be sourced in the scarce foreign currency. Mozambique and South Africa were forced to cut electricity supplies to Zimbabwe after the country failed to settle outstanding debts due to foreign currency shortages (AfDB/OECD, 2004). Liquid fuel supplies from Libya were cut in 1999 due to the scarcity of foreign currency (AfDB/OECD, 2004). It is not in dispute that the current liquid fuels shortages being experienced are due to the foreign currency scarcity.

Poor water quality and sanitation in most urban areas are a result of foreign currency shortages. There is not enough foreign currency to purchase the needed water purification chemicals and equipment. All these mentioned issues impact negatively on the tourism industry. Yet, the tourism sector is a sector which can generate the much-needed foreign currency to deal with some of these challenges. The country is experiencing an unstable foreign currency supply, resulting in fuel supply shortages and frequent electricity power cuts. Foreign currency is needed to settle electricity debts, replace worn-out machinery at the Kariba electricity power station and to purchase fossil fuels. The foreign currency can be increased through the tourism industry. International tourism is a significant foreign currency earner (Sanderson & Pierre, 2017; Brida, Carrera & Risso, 2008). According to the AfDB/OECD (2004), the decline in Foreign Direct Investment (FDI) and capital inflows resulted from the poor macroeconomic policy and the socio-political environment. Accurate tourism forecasts can help investors in deciding which tourism activities to fund and venture into. Tourism volatility models will assist in quantifying the risk associated with investing in the tourism sector. According to the Migration and Tourism Report (2015), the Zimbabwean tourism sector experienced an increase in international tourist arrivals from the 1.2 million recorded in 2009 to 2.1 million recorded in 2015. Besides the noticeable increase, the sector is facing some revival challenges as commercial banks are failing to fund tourism projects in the country as the projects are considered long-term projects that have a long payback period (The World Bank, 2013). The banks opt for short-term projects such as small businesses (lodges) that have a short payback period. This has slowed down the progress of the sector and this has negatively affected various economic sectors in the country. Sanderson and Pierre (2017) noted that lack of direct flights, hyperinflation, fuel shortages and erratic supply of amenities; making destinations expensive with compromised safety and security. All these are contributing factors to the decline and volatility in the tourist arrivals in Zimbabwe. Tourism remains highly sensitive to the bad publicity that Zimbabwe has attracted (AfDB/OECD, 2004).

Muchapondwa and Pimhidzai (2011) and Karambakuwa, Shonhiwa, Murombo, Mauchi, Gopo, Denhere Mudavanhu (2011) studied on Zimbabwe's tourism and concentrated on tourism determinants. However, the prediction of future tourist arrivals and volatility was left unattended, yet the analysis leads to better planning and resource allocation in the country. In coming up with effective tourism policies, the government, tourism stakeholders, airline companies, accommodation companies and transport managers make use of accurate tourism forecasts that quantify future uncertainties. Investors make use of tourism volatility forecasts whenever they are interested in investing, and constantly monitor the market. The Zimbabwe Tourism Authority (ZTA) is predicting future international tourist arrivals using the regression method that may suffer from spurious regression and poor forecasting and failures, according to Song and Li (2008). The model does not incorporate future uncertainty and seasonality in tourist arrivals. The Autoregressive Moving Average (ARMA) models or Autoregressive Integrated Moving Average (ARIMA) or seasonal ARIMA (SARIMA) models and the Generalised Autoregressive Heteroskedasticity (GARCH) models give good short-term forecasts and a clear visualisation of future volatility. The aim of the paper is to develop bootstrap prediction intervals for international tourism demand and volatility after modelling with an ARMA-GARCH model. Bootstrap prediction intervals cater for uncertainty due to parameter estimation as indicated by Pascual, Romo & Ruiz (2006). Tourism volatility has a strong, lifelong effect on the economy. A GARCH process will give a picture of the associated volatility and goes the extra mile to foresee future tourism volatility. Many researchers (Claveira & Torra, 2014; Lee, Song & Mjelde, 2008; Chu, 2008; Chen, 2006; Yeung & Law, 2005) concluded that these time series forecasting methods produce satisfactory forecasts at minimum costs with sensible benefits.

Literature review

More research has been done on international tourist arrivals in developed countries than in developing countries, and tourist arrivals vary with the destination (Rogerson, 2007; Xiao & Smith, 2006). Ample studies addressing, accurate tourist arrivals modelling, international tourism volatility and forecasting exist (Karambakuwa et al., 2011; Muchapondwa & Pimhidzai, 2011, Chang & McAleer, 2012; Saayman & Saayman, 2010; Schulze & Prinz, 2009; Lee et al., 2008; Chu, 2008a; Hoti, León & McAleer, 2006, Liu, Su & Ge, 2005; Shareef

& McAleer, 2005). ARMA/ARIMA/SARIMA models are commonly used in modelling tourism demand. An ARIMA model was applied to Australian tourism. The data was on tourists from Malaysia, Singapore and Hong Kong by Lim and McAleer (2002) and the models captured all the dynamics of the data. Petrevska (2017) noted that an ARIMA(1,1,1) model was the best for Macedonia's international tourism data. A 13.9% rise in future international tourist arrivals was suggested by the model. Saayman and Saayman (2010) modelled tourism demand for South Africa using tourists' data from Germany, France, Great Britain, Netherlands and the USA. The fitted SARIMA models outperformed the Holt-Winters models. Peiris (2016) fitted a SARIMA $(1,0,16)(36,0,24)_{12}$ model to Sri Lanka's tourism data. The model captured the seasonality in the data. Borhan and Arsad (2015) fitted a SARIMA model to the Malaysia's tourism demand after noting seasonality in the data. The SARIMA$(1,1,1)(1,0,1)_{12}$, SARIMA$(1,0,0)(1,0,0)_{12}$ and SARIMA$(0,1,1)(0,1,1)_{12}$ models fitted well to the US, Japan and South Korea tourism data, respectively. South Korea, Japan and the USA are considered as the major tourism sources for Malaysia. A possible increase in tourist arrivals from South Korea and the US was noted. The above-mentioned studies used the Box-Jenkins approach employed in this study. Conditional volatility models such as the Generalised Autoregressive Conditional Heterokedasticity (GARCH) family of models are good at modelling tourism demand volatility (Shareef and McAleer, 2007; Kim and Wong, 2006; Shareef and McAleer, 2005 and Chan, Lim & McAleer, 2005). From the multivariate GARCH model employed by Chan et al. (2005), in modelling tourism demand volatility for Australia from its main tourism sources (the USA, UK, New Zealand and Japan), the presence of interdependent effects in the conditional variances among the mentioned countries was noted. Shareef and McAleer (2005) used the GARCH(1,1) and GJR(1,1) in modelling the volatility in international tourism data and the growth rate of tourism data for Cyprus, Fiji, Barbados, Seychelles, Dominica and Maldives. The GARCH models were fitted to the ARMA(1,1) model residuals and the model parameters were all significant. The conditional mean and variance estimate from the models were found to be statistically significant and similar across all the countries.

In Portugal, Daniel and Rodrigues (2010) modelled tourism seasonality and volatility from Spain, Netherlands, Germany and France, which are the main tourism source markets for Portugal. The ARIMA(1,1) model was considered as the mean equation and the model parameters were all significant for the considered countries. The GARCH(1,1) model was appropriate for Germany and France's tourism volatility and it was noted that both negative and positive shocks had similar effects on the tourism volatility. An ARIMA(3,1,4)-GARCH (1,1) model was found to be appropriate for Cambodia's international tourist arrivals by (Chhorn & Chaiboonsri, 2018). The model was good in quantifying tourism volatility. The GARCH(1,1) model was used by Fernando, Bandara, Liyanaarachch, Jayathilaka & Smith (2013) in modelling Sri Lanka's tourism volatility and the model proved to be good for quantifying uncertainty in future tourist arrivals. For the same country, Priyangika, Pallawala, Sooriyaarachchi (2016) concluded that an ARCH(1) model was the best in capturing Sri Lanka's tourism volatility. Because of the ability of the GARCH family of models to capture and quantify tourism volatility, they are adopted in this study. Efron and Tibshirani (1979) introduced the bootstrap method, and according to Pascual et al. (2006), they dealt with uncertainty due to parameter estimation. The bootstrap method was also employed in ARCH models by Reeves (2000) to deal with parameter uncertainty. The bootstrap method is adopted in this paper to cater for uncertainty in tourism model parameter estimates.

Methodology

Statistical methods used

The original number of international tourist arrivals are denoted by Y_t, and a logarithm transformation is applied to tame the variance. The log transformed series is denoted by Z_t. The transformation is expressed as follows:

$$Z_t = \log(Y_t)$$

The univariate forecasting models being adopted in this paper makes uses of stationary data. The Augmented Dickey-Fuller (ADF) (1979) test is used to examine the presence of a unit root on Z_t before fitting an appropriate model. Time series plots are used to visualise the behaviour of international tourist arrivals. The Box-Jenkins (1970) approach is used in fitting the appropriate model. The ARMA/ARIMA model is used to predict future international arrivals while the GARCH process is used in predicting future uncertainty in international tourist arrivals. An ARMA(p,q) model is combination of an AR(p) and MA(q) model. Using the logarithm of monthly international tourist arrival series (Z_t), an ARMA(1,1) model can be presented as:

$$Z_t = \phi Z_{t-1} - \theta e_{t-1} + e_t,$$

where e_t is error term and the AR and MA model parameters are denoted by ϕ and θ, respectively. The ARIMA(p,d,q) model is denoted by the formula:

$$\phi_p(B)\nabla^d Z_t = \theta_q(B)e_{t,} \quad e_t \sim N(0, \sigma_t^2)$$

where B, ϕ_q, θ_q, ∇^d and e_t is the backward shift operator, AR model parameter vector, MA model parameter vector, difference operator and the error term, respectively. The logarithm of monthly international tourist arrival series is represented by (Z_t). The bootstrap method for ARIMA models proposed by Pascual et al. (2006) is adopted because of its ability to incorporate variability in parameter estimation into prediction intervals without requiring the backward representation of the process. The 95% confidence interval will be considered on the model since it the widely used, apart from being sensible.

The Akaike Information Criterion (AIC) (Akaike, 1974) is used in model selection, for both ARMA/ARIMA/SARIMA and GARCH model. The Box-Ljung test is used to test the randomness of model residuals and the presence of ARCH effect. Normality test of residuals is done using the Jarque Bera (JB) test given by the formula:

$$JB = n\left[\frac{skewness^2}{6} - \frac{(kurtosis)^3}{24}\right],$$

where n is the number of observations. The forecasting performance of the mean equation model is examined through the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The MAE is expressed as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{Z}_i - Z_i\right|,$$

where $\hat{Z}_i$ represents estimated values, Z_i represents original values (log-transformed series) and n is the number of observations.

ARCH/GARCH models

The ARMA(1,1) and ARIMA(p,d,q) models mentioned above assumes homoscedasticity on the error terms, which may seem impossible when dealing with international tourist arrivals data in a country like Zimbabwe. This prompts the adoption of the ARCH and GARCH models proposed by Engle (1982), Bollerslev (1986) and Taylor (1986). The ARCH/GARCH model is fitted to the ARMA/ARIMA/SARIMA model's residuals if there is evidence of the presence of the ARCH effect. The ARCH model is denoted by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i e_{t-i}^2$$

Where ω and α_i are model parameters. The GARCH (p,q) model is represented by the formula:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, e_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-i}^2$$

where $\omega > 0, \alpha \geq 0$, $\beta \geq 0$, $(\alpha + \beta) < 1$ and the constant variance is denoted by σ^2 . The GARCH family of models will be fitted under the assumption that the model residuals follow a Normal, Generalised Error Distribution(GED) or a Student's *t* Distributions (STD).

Bootstrap prediction intervals procedure

In bootstrapping, first the GARCH(1,1) model is used to generate T future observations denoted by $V_T(V_T = v_t, v_{t+1}, \dots, v_T)$. The distribution of V_T is f and the associated conditional variance σ_T is then estimated. New GARCH(1,1) parameters denoted by $\hat{\theta} = (\hat{\omega}, \hat{\alpha}, \hat{\beta})$ are estimates and they mimic the original parameters denoted by $\theta = (\omega, \alpha, \beta)$. The model residuals denoted by $\hat{e}_t$ $(t = 1, 2, 3, \dots, T)$ are calculated while the conditional variance will be computed by the formula

$$\sigma_t^2 = \frac{\hat{\omega}}{1-\hat{\alpha}-\hat{\beta}} \; (t = 1,2,3, \dots, T).$$

Bootstrapping with replacement will be applied to come up with new volatility values denoted by $V_T^*(V_T^* = v_t^*, v_{t+1}^*, \dots, v_T^*)$ from the distribution $\hat{f}$ and are approximately equal to $V_T(V_T = v_t, v_{t+1}, \dots, v_T)$. The bootstrap replicates (V_T^*) are generated by the recursive formula:

$$v_t^* = e_t^* \sigma_t^{*2},$$
$$\sigma_t^{*2} = \hat{\omega} + \hat{\alpha} v_{t-1}^{*2} + \hat{\beta} \hat{\sigma}_{t-1}^{*2},$$

where $t = 1,2, \dots, T$ and e_t^* represents the error term.

The future bootstrap forecasts will be generated by the following equations:

$$v_{k+T}^* = e_{k+T}^* \hat{\sigma}_{k+T}^{*2},$$
$$\sigma_{k+T}^{*2} = \hat{\omega} + \hat{\alpha}^* v_{k-1+T}^{*2} + \hat{\beta}^* \hat{\sigma}_{k-1+T}^{*2},$$

where e_{k+T}^* are random errors.

According to Pascual et al. (2006), the variable σ_T^{*2} incorporates variability due to parameter estimation and takes into account the state of the process when predictions are made. The variable σ_T^{*2} can be expressed as:

$$\sigma_T^{*2} = \frac{\hat{\omega}^*}{1 - \hat{\alpha}^* - \hat{\beta}^*} + \hat{\alpha}^* \sum_{i=0}^{T-2} \hat{\beta}^{*i} \left(v_{T-1-i}^2 - \frac{\hat{\omega}^*}{1 - \hat{\alpha}^* - \hat{\beta}^*} \right)$$

Finally, the quantiles of the bootstrap distribution are used to come up with prediction intervals.

Data analysis and discussion of results

Data

To model international tourist arrivals and volatility, Zimbabwe's monthly international tourist arrivals data for the period January 2000 to June 2017 obtained from the ZTA is used. The in-sample period is from January 2000 to December 2016 and is used for the estimation of the ARMA/ARIMA and GARCH models, while the out-of-sample period assists in comparison with out-of-sample forecasts from January 2017 to June 2017. The study period is based on the available data.

Descriptive statistics of the data

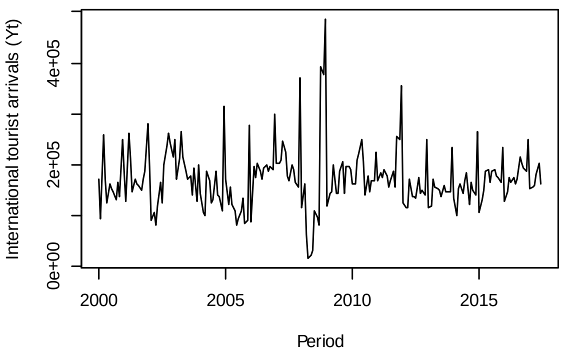
The summary statistics of both the monthly international tourist arrivals (Y_t) and the logarithm transformed series (Z_t) are done using the R package.

Table 1: Summary Results for Y_t and Z_t.

Series	Mean	Median	Max	Min	Std.Dev	Skewness	Kurtosis
Y_t	172040	167126	485900	15511	59403	1.33	4.9
Z_t	11.99	12.03	13.09	9.65	0.39	-1.86	12.78

Results in Table 1 show that the mean of Y_t and Z_t are 172040 and 11.99, respectively. The series Y_t are positively skewed as indicated by the skewness value (1.33) while Z_t are negatively skewed according to skewness value (-1.86). It can further be noted that the maximum and minimum absolute number of international tourist arrivals during the study period were 485900 and 15511, respectively.

The time series plots are used to characterise the behaviour of both Y_t and Z_t and are displayed in Figure 1.



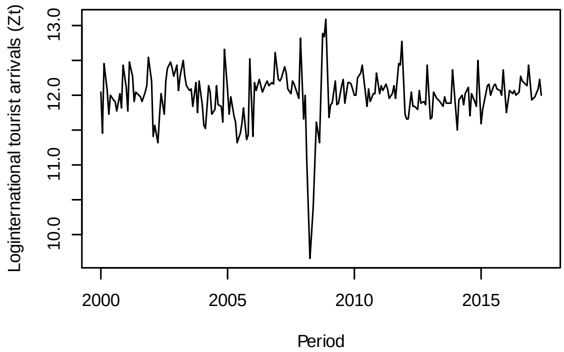


Figure 1: Time series plots of Y_t and Z_t series

Both series exhibit tourism volatility as seen in Figure 1. The series Z_t looks smoother and it mimics the original series although it looks smoother. About 80.7% of Zimbabwe's international tourist arrivals are from Southern and Central Africa (Zimbabwe-Visitor Exit Survey Report (2015/16), where winter and summer seasons are similar, hence total international tourist arrivals for the country are not seasonal as indicated in Figure 1. It can be noted from Figure 1 that tourists increased around 2002 due to ZTA marketing strategies. The signing of the Approved Destination Status Memorandum of Understanding which facilitated the movement of Japanese, Chinese, Indian and Malaysian citizens (tourists) as well as the introduction of a direct flight to Beijing by the Air Zimbabwe in 2004 increased international tourist arrivals in that year. A decline in the year 2005 was attributed to the negative publicity of Zimbabwe as a country in major tourism source markets as well as a deteriorating economy.

It is observed from Figure 1 that both the series Y_t and Z_t seems to be stationary despite the existence of some high spikes around the year 2008. There is a major drop around year 2008 due to the recession in tourism source markets such the UK and the USA between the years 2008 and 2009, the negative media publicity of political violence in Zimbabwe after the

March 2008 Harmonised Elections (Zimbabwe Tourism Trends and Statistics Report, 2008), fuel shortages, price hikes and shortages of commodities in most Zimbabwean shops. High peaks around 2009 were a result of the inclusive and more stable government formed in February 2009 and the introduction of a multiple currency system. Tourists increased by 53% in the year 2009 due to the ZTA's tourism campaign and a better political envinronment (Karambakuwa et al., 2011). Tourist arrivals declined in the year 2012 as a result of border facilitation issues and poor road infrastructure since most of the tourists from Africa use road transport (Tourism Trends and Statistics, 2012).

Stationarity test

To ascertain stationarity visualised in Figure 1, the ADF test is conducted on Z_t before fitting a time series model. The Dickey-Fuller test statistic (-8.33) associated with the p-value of 0.01 suggest the rejection of the null hypothesis of the presence of a unit root. It can be concluded that the data is stationary.

ARMA/ARIMA model identification and fitting

Since the data is stationary, the ACF and PACF plots are constructed to identify the suggested model from the data.

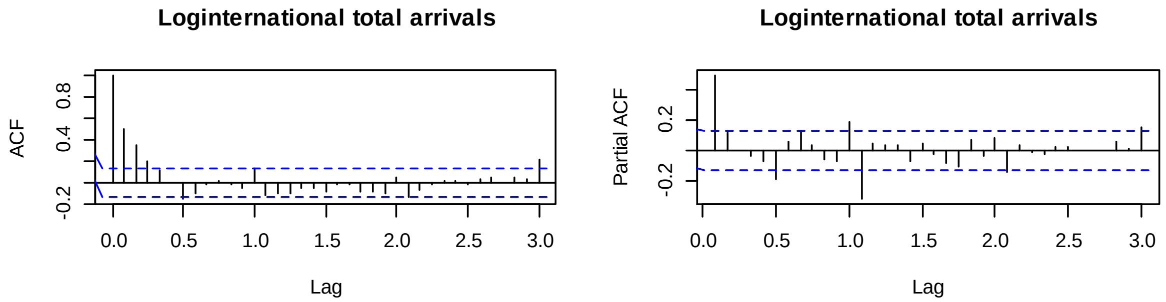


Figure 2: The ACF and PACF plots of Z_t

ACF and PACF of Z_t exhibited in Figure 2 suggest the need for an ARMA(1,1) model as a tentative model. The Extended Autocorrelation Function (EACF) are further used in the identification the exact AR(p) and MA(q). The EACF results are shown in Table 2.

Table 2: The EACF of Z_t.

AR/MA	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	X	x	x	O	o	x	x	o	O	O	O	o	x	o
1	x	o	o	o	o	x	o	o	o	o	o	o	x	o
2	x	o	o	o	o	x	o	o	o	o	o	o	x	o
3	X	o	o	O	O	x	o	o	o	o	o	o	x	x
4	X	x	o	O	X	x	o	O	O	O	O	o	x	o
5	X	o	o	X	X	x	o	O	O	O	O	o	x	o
6	x	x	x	o	x	x	o	o	o	o	o	o	x	x
7	X	x	x	O	O	o	x	O	O	O	O	o	x	o

An ARMA(1,1) model is being suggested by the EACF of Z_t results displayed in Table 2. An ARMA(1,1) model is fitted along with other models and the AIC of the fitted models are displayed in Table 3.

Table 3: The AIC of fitted models

Model	**AIC**
ARMA(1,1) with constant	143.07
ARIMA(0,0,1) with constant	159.82

ARIMA(1,1,1) with constant	147.33
ARIMA(1,0,0) with constant	143.09

The ARMA(1,1) model with a constant has the lowest AIC value of 143.07, as shown in Table 3 and is considered as the mean equation for the Zimbabwe's monthly international tourist arrivals. The optimal parameters of the model are summarised in Table 4.

Table 4: The ARMA(1,1) model parameters

	ϕ	θ	Constant
Coefficient	0.7356	-0.4894	11.9924
Standard Error	0.0961	0.1174	0.0504
p-value	<0.0001	<0.0001	<0.0001

Table 4 exhibits the ARMA(1,1) model parameters which are all statistically significant. In modelling the volatility in international tourism data and the growth rate in Small Islands (Cyprus, Fiji, Barbados, Seychelles, Dominica and Maldives), Shareef and McAleer (2005) fitted an ARMA(1,1) model similar to the one fitted in this study with significant parameters. Residual diagnosis is done, whereby the Box-Ljung and Jarque Bera tests are used to test autocorrelation and normality of model residuals. According to the Box-Ljung test statistic (18.241) which is associated with a p-value of 0.38236, which is above 0.05, thus the null hypothesis of no autocorrelation on the model residuals is not rejected. The Jarque Bera test results indicated that the residuals are normally distributed at p = 0.0474. For visualisation purposes, Figure 3 displays the Q-Q and ACF plot of residuals.

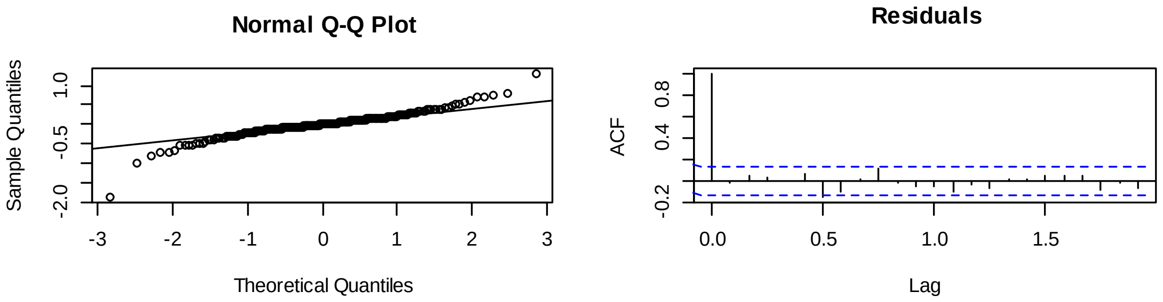


Figure 3: Q-Q and ACF plots of model residuals

Figure 3 concurs with the Box-Ljung, and Jarque Bera test as the exhibited graphs confirm the randomness and normality of the model residuals. The ACF plot is like that of a white noise process. Furthermore, the forecasting performance of the selected model together with the other fitted models are examined through the RMSE, MAE and MAPE. Table 5 displays forecasting performance measures of the fitted models.

Table 5: Forecasting performance measures

Model	RMSE	MAE	MAPE
ARMA(1,1) with constant	0.333122	0.226884	1.915095
ARMA(1,2) with constant	0.333140	0.227644	1.921450
ARIMA(1,1,1) with constant	0.335081	0.229375	1.935161

It is evident from Table 5 that the ARMA(1,1) model with a constant is the best model in forecasting international tourist arrivals for Zimbabwe as supported by lower values of RMSE, MAE and MAPE. The ARMA(1,1) model adhered to all model diagnostic tests; hence, it is used to estimate out-of-sample Zimbabwe's international tourist arrivals for the next 30 months. An anti-logarithm is applied to come up with real tourism forecasts. Table 6 displays estimated future tourism values.

Table 6: Future Zimbabwe international tourism forecasts from ARMA(1,1) model

Month	Forecasts	Month	Forecasts	Month	Forecasts
Jul-17	207976	May-18	187223	Mar-19	188360
Aug-17	221732	Jun-18	182398	Apr-19	181405
Sep-17	206451	Jul-18	205702	May-19	187637
Oct-17	213744	Aug-18	201794	Jun-19	182179
Nov-17	217395	Sep-18	218116	Jul-19	199443
Dec-17	246758	Oct-18	218031	Aug-19	197838
Jan-18	239845	Nov-18	228185	Sep-19	209176
Feb-18	219983	Dec-18	239798	Oct-19	217657
Mar-18	209286	Jan-19	228882	Nov-19	221707
Apr-18	190578	Feb-19	198598	Dec-19	238492

The results in Table 6 shows slow average growth in Zimbabwe's international tourist arrivals with the country expecting high numbers around December. Petrevska (2017) obtained similar findings when the fitted ARIMA(1,1,1) model indicated a 13.9% increase in Macedonia's international tourism data. Responsible authorities need to make the necessary accommodation, food and transport arrangements for higher numbers of tourists in December. The results highlight the need for continuous aggressive marketing by the ZTA so that the country receives more international tourists as this will improve the country's foreign currency earnings. The ZTA could also market all tourist attraction sites in Zimbabwe to avoid underutilisation of these sites.

ARCH effects

The ARCH effect is tested on the ARMA(1,1) model residuals (squared residuals) before proceeding with volatility modelling. The Box Ljung test statistic of 62.304 associated with a p-value of 0.003115, suggesting the presence of ARCH effects, thus we reject the null hypothesis of absence of ARCH effect. This means volatility in Zimbabwe's monthly international tourist arrivals is varying with time, suggesting the need for a GARCH process.

GARCH model selection and fitting

Different combinations (see Table 7) of GARCH processes are fitted under different distributional error assumption (Normal, GED and STD) using the ARMA(1,1) model residuals. The AIC is used to select the best model.

Table 7: AIC of GARCH models

GARCH Model	AIC
GARCH(1,1) –norm	0.32865
GARCH(1,1)-std	0.27689
GARCH(1,1)-ged	0.28038

The GARCH(1,1) model under STD fits well to the mean equation residuals as indicated by a lower AIC value of 0.27689 shown in Table 7. The optimal parameters of the GARCH(1,1)-std model are summarised in Table 8.

Table 8: GARCH(1,1)-std model parameters

Coefficients	Estimate	Std.Error	t-value	Pr(>|t|)

ω	0.02445	0.03060	2.41362	0.01125
α_1	0.66389	0.64810	3.50301	0.00817
β_1	0.25808	0.07411	3.48263	0.02614
Shape	3.78768	1.01782	3.72136	0.00020

All the GARCH(1,1)-STD model parameters exhibited in Table 8 are statistically significant at the 5% as indicated by all p-values values, which are below 0.05. It can be observed that the persistent level ($\alpha_1 + \beta_1 = 0.92197$), is close to one indicating long periods of the persistence of shocks to volatility in the future. These results are similar to those of Daniel and Rodrigues (2010) who concluded a long-run volatility persistence in Portugal. In Taiwan and Sri Lanka, Chang and McAleer (2009) and Jegajeevan (2012) also noted high persistent levels that fades away gradually. The ARCH coefficient ($\alpha_1 = 0.66389$) is high indicating unstable short-term volatility. This suggest that the volatility will react intensely to tourism shocks. The value of β_1 (0.25808) implies that the tourism shocks to conditional variance will last longer before dying off. Hence persistent volatility needs to be dealt with in Zimbabwe. The residual diagnostics of the GARCH(1,1)-STD model are done through the Ljung-Box test and the normal Q-Q plot.

Table 9: Weighted Ljung test on standardized and standardized squared residuals

Weighted Ljung-Box Test on Standardized Residuals		
Weighted	Statistic	p-value
Lag[1]	0.06684	0.79604
Lag[2*(p+q)+(p+q)-1][2]	0.401250	0.99998
Lag[4*(p+q)+(p+q)-1][5]	2.61984	0.93968
Weighted Ljung-Box Test on Standardized Squared Residuals		
Weighted	Statistic	P-value
Lag[1]	0.00366	0.95172
Lag[2*(p+q)+(p+q)-1][5]	0.98965	0.86199
Lag[4*(p+q)+(p+q)-1][9]	2.3857	0.85436

According to the results displayed in Table 9, there are no serial autocorrelations in the standardised residuals since all the Ljung-Box test statistic's probability values exceed 0.05. ARCH LM test results are also displayed in Table 10.

Table 10: Weighted ARCH LM tests

	Statistic	Shape	Scale	**p-value**
ARCH Lag[3]	0.48442	0.500	2.000	0.48644
ARCH Lag[5]	2.18117	1.440	1.667	0.43258
ARCH Lag[7]	2.50984	2.315	1.543	0.61036

According to Table 10 results, there are no dependencies in the model residuals. This conclusion is derived from the p-values, which all exceeds 0.05 at lag 3, lag 5, and lag 7. Normality of the residuals is checked through the density and Q-Q plot displayed in Figure 5.

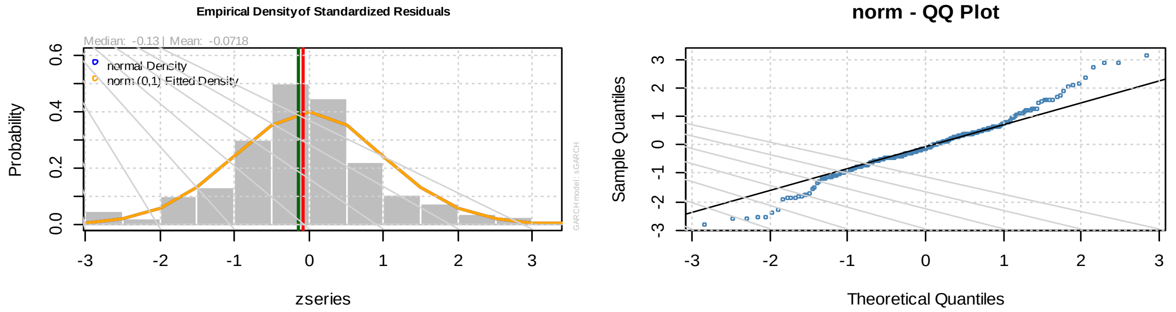


Figure 5: Density and Q-Q plot

It can be concluded that both the density and Q-Q plot of the standardised residuals depicts a normal distribution series even though a little divergence is seen at both the start and end of the Q-Q plot. Since the residuals of the GARCH(1,1)-std behave well, bootstrapped future volatility forecasts are constructed. Figure 6 shows 500 bootstrapped volatility forecasts together with the prediction intervals.

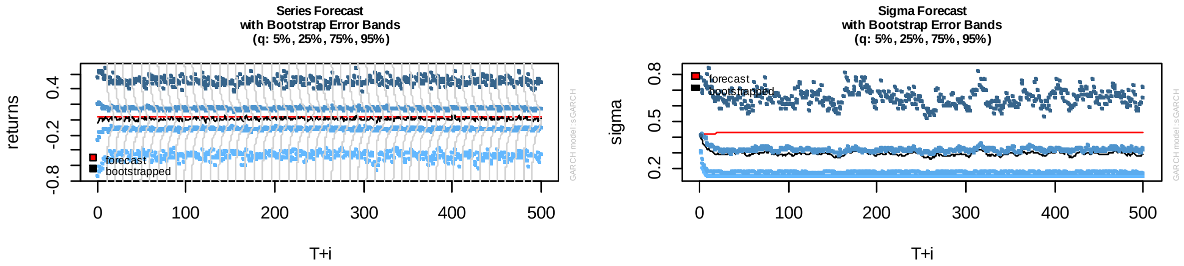


Figure 6: Bootstrap prediction intervals for tourism volatility

The bootstrapped volatility forecasts and the boundaries indicate minimal uncertainties in the international tourist arrivals. The bootstrap prediction intervals allow better assessment of future tourist arrivals uncertainty and provide supplementary information that can be used in decision-making and planning purposes. Investors may invest in tourism related activities considering the minimal risks exhibited by bootstrap forecasts. However, the ZTA, in partnership with the government could continue engaging in bilateral trade, come up with effective and friendly policies to deal with future tourist arrivals uncertainties. The ZTA need to market Zimbabwe to all the new and young generations and woo investors in all the source markets.

An ARMA(1,1) model fitted well to the data and the forecasts indicated that Zimbabwe's international tourist arrivals with grow relatively slowly. The information is needed to plan for food, accommodation facilities and transport facilities to be put in place to cater for that level of expected growth. However, effective marketing strategies are needed so that a significant increase in international tourist arrivals is achieved. The GARCH(1,1) model suggest that tourism shocks will lead to volatility and the impact on tourism demand will have a relatively long-lasting effect. Minimal uncertainties in the international tourist arrivals are suggested by the bootstrap prediction intervals, implying minimal risk.

Implications and conclusion

Zimbabwe's international tourism data for the period 2000-2017 was used in modelling tourism demand and volatility. The logarithm of the monthly international tourist arrivals is stationary and fits well to the ARMA(1,1) model. The data are not seasonal since the bulk of the tourists are from Southern Africa, and they visit Zimbabwe any time of the year because of similar temperatures/climate across Southern African countries. This is unlike tourists from Europe who visit Zimbabwe during their winter season making data for certain tourist attraction centres frequented by Europeans, seasonal. The ARMA(1,1) model indicated a small increase in Zimbabwe's international tourist arrivals for the next 30 months. Enough accommodation and transport facilities are needed to cater for this expected small increase in international tourist arrivals in the next years. An increase in international tourist results in an increase in foreign currency earnings. These will be the first few steps to one solution of the foreign currency-related problems in the country.

The GARCH(1,1) model under the STD assumption is a better model for the ARMA (1,1) model residuals. Similar findings were obtained by Shareef and McAleer (2005) who modelled tourism demand and volatility in Small Islands (Cyprus, Fiji, Barbados, Seychelles, Dominica and Maldives). The fitted GARCH(1,1) model catered for volatility persistence witnessed in the international tourism series. The GARCH (1,1) model offers an appropriate way to quantify the conditional volatility of Zimbabwe international tourism series. According to the research findings, the persistence of the tourism shocks in the long-run was 0.92197, suggesting that unexpected tourism shocks will significantly impact the Zimbabwe international tourist arrivals for longer periods. Unexpected tourism shocks will impact on the Zimbabwe international tourist arrivals, the economy, investment opportunities and the employment sector among other sectors. For the Zimbabwe tourism industry to remain relevant, new tourism products could be developed together with new attraction centres, whilst embarking on effective marketing strategies to lure even more international tourists from abroad. This will increase the much-needed foreign currency in the country for reviving the economy. The inclusion of bootstrap prediction intervals in modelling international tourism demand and volatility helps to quantify the uncertainty in tourist arrivals' models. Bootstrap prediction intervals for tourism volatility indicated minimal future uncertainty. This calls for major tourism stakeholders to develop new policies to deal with the foreseen uncertainty and to make Zimbabwe a destination of choice. The ZTA and government ought to market all the country's tourism sites to all potential tourists in all tourism source regions to attract FDI. This will help in employment creation, increased GDP, and foreign currency earnings.

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