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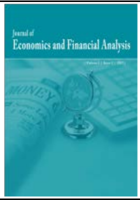

# Forecasting Value Added Tax Revenue in Ghana

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**Abstract**

*Governments need accurate tax revenue forecast figures for good economic planning but there seems to be no consensus on which method is the most suitable to deliver reliable results leading to differences in the choice of technique from one country to another. This study therefore forecasts Ghana's Value Added Tax (VAT) Revenue by comparing two methods, ARIMA with Intervention and Holt linear trend methods to establish the one with more precise predictive powers for VAT Revenue. Monthly VAT revenue data from the year 2002 to 2019 is used in the analysis. The findings show that ARIMA with Intervention method outperformed the Holt linear trend model in terms of accuracy and precision. A comparison of predicted results from the ARIMA with intervention model from 2017 to 2019 with Ghana Revenue Authority's VAT revenue targets based on their in-house forecasting model for the same period reveals that the ARIMA with intervention approach performs better than the in-house forecasting model of the VAT authority. In this case, the study recommends the ARIMA with intervention method to the tax authority for consideration in its forecasting.*

**Keywords:** *Value Added Tax (VAT); Forecasting; ARIMA; Holt linear trend; Fiscal Policy Ghana.*

**JEL Classification:** *C53, H20.*

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## 1. Introduction

Revenue mobilization is critical for fiscal policy implementation, particularly in developing countries with chronic budget deficit challenges. Taxation is considered as a better resource revenue mobilization tool than other alternatives such as money creation and debt financing. Government revenue in Ghana therefore depends largely on taxes as in other African countries.

In recent times, Value Added Tax (VAT) has evolved as the main workhorse of taxation in developing countries (Le et al, 2016). Heady (2002) observed the use of VAT to mobilize sales tax revenues among OECD countries therefore the VAT becomes the sales tax of choice in OECD countries. While these countries continue to depend heavily on income tax collection, the VAT revenues have risen steadily in both absolute and relative terms. In these countries, the general consumption taxes which are dominated by VAT have seen sharp increases in yields from 12 percent of the total tax revenues in 1965 to 18 percent in 2000 (Heady, 2002).

Given the relative success of the OECD countries in the VAT revenue mobilization, many developing countries now make good use of the VAT to also mobilize revenue as it is seen to be more cost effective in mobilization and productivity. According to the IMF, the VAT has become a key source of government revenue in over 120 countries. About 4 billion people, 70 percent of the world's population, now live in countries with VAT, and it raises about $18 trillion in tax revenue, thus about one-quarter of all government revenue (Ebrillet al., 2001).

Ghana's case is not different from the foregoing as VAT contribution to Total Government Revenue has been between 20 percent and 30 percent since its inception from 1995 to date. Therefore, VAT is considered a major source of government tax revenue in Ghana which forms about as at 2019.

In view of the relevance of VAT in government's fiscal policy, it is imperative to precisely forecast its yield for effective budget planning. As such getting a good forecasting model to determine this predictive power with minimum errors is step in the right direction. Therefore, this study aims at using two comparable forecasting techniques; the ARIMA with Intervention and Holt Winter's models to predict the revenue generating powers of the VAT and ascertain which of the two is superior. Additionally, the results of the superior method is compared with the Ghana Revenue Authority's in-house forecasting model predictions in terms of their target revenue figure over the period 2017 to 2019 where data exist. The outcome of this study would be of much policy relevance to the tax authorities is their revenue forecasting processing as it offers alternatives to their in-house method.

The rest of the paper is organised as follows: section two deals with a brief literature, section three treats the estimation model and the data source. Section four reports the forecasting results and the associated discussions and then section five concludes the study and provides the policy suggestions.

## 2. Brief Literature

Although different scholars advocate different forecasting models, many of them point to outcomes of econometrics techniques as more accurate with minimum biases to revenue forecasts than the simple judgemental approaches. The use of time series methods for revenue forecasting has attracted many researchers in testing for their efficiency. Some of the methods are the ARIMA models (see Baguestani and McNown, 1992; Favero and Marcellino, 2005; Nazmi and Leuthold, 1988; Fullerton, 1989; Koirala, 2011; Brojba, Dumitru, and Belciug, 2010; Slobodnitsky and Drucker, 2008), the Vector Auto-Regressive (VAR) model (see Baguestani and McNown, 1992; Favero and Marcellino, 2005), the Random walk model (Favero and Marcellino, 2005); the Trend models (Kong; 2007), Regression models (see Nazmi and Leuthold, 1988; Fullerton, 1989; Kong, 2007;Irizepova, 2016) and the Holt-Winters model (Fomby, 2008; Makananisa, 2015).

Gardner and McKenze (1985) test the Holt linear trend and damped trend in forecasting time series to know which of the two approaches produces a more accurate forecast. They develop an exponential smoothing model to damp erratic trends. The data used consist of 181 yearly, 203 quarterly and, 617 monthly series. 114 series were demographic, 319 macroeconomic series, 302 series were company data, and 236 series is of industry sales. The study reveals that accurate forecast can be produced with Holt linear trend model when the trend of the time series observations is not erratic. However, for erratic trends, developing a model to damp the trend produces a more accurate forecast compared to smoothing models based on a linear trend.

Nikolov (2002) forecasts tax revenue with the intervention time series model by using the Box-Jenkins model selection approach and continued with the intervention effects analysis. This work was done with monthly tax revenue data for the period January 1998 to July 2002, from the Republic of Macedonia. The study recommends that the model is good for forecasting but because the variance of the forecasts in time series models becomes large over time, it will produce good forecast results for only a few time units ahead and not for longer periods.

Sologoub et al (2003) apply a stationary time series approach to establish a long-term relationship between VAT base and VAT productivity. They also use the ARIMA model for a monthly data to forecast VAT revenue in the short run. They conclude that ARIMA is very consistent with the projections made by the government of Ukraine for its budget. In addition, they argue that VAT refund, debt, numerous tax exemptions and, low VAT compliance have the potential of complicating the VAT revenue forecasting in Ukraine.

Slobodnitsky and Drucker (2008) forecast monthly VAT revenue data for Israel from January, 1987 to December, 2006 and compared the results with a co-integration estimation. They use the ARIMA method and adjudged it to be better and precise than the co-integration results since the ARIMA specification had lesser absolute deviations. A further comparison of ARIMA and unrestricted linear regression model by Fullerton (1989) favoured the latter because it had lesser Root Mean Squared Error.

It is worthy to note that comparisons of the forecasting performance of different methods frequently find that ARIMA outperforms other models at least in the short run. It can also be deduced from the literature that there is no consensus on which method can precisely predict the fiscal variable. It is therefore suggested that each forecasting method should be considered on case by case bases. Therefore in view of dearth of studies on tax revenue forecasting in Ghana, this study attempts to model the VAT Revenue Forecasting in Ghana to fill the void in the literature.

## 3. The Model

The forecasting model, ARIMA with intervention in this study is based on the works of Darkwah et al (2012) and Edzie-Dadzie (2013) with modifications. The Holt linear trend model is also based on the study by Gardner and Mckenzie (1985) with some adjustments.

### 3.1. The Auto-Regressive Integrated Moving Average (ARIMA) Model

The ARIMA model is appropriate for time series of at least 50 observations. Given a time series; $X_1, X_2, X_3, \ldots X_t$ where $t$ is the time and $X$ is the observations, in an attempt to fit an ARIMA model to a time series data, the first step is to check for stationarity. A stochastic process $X_t$ is said to be strictly stationary if the joint distributions of $X_{t1}, X_{t2}, \ldots. X_{tn}$ and $X_{t1-m}, X_{t2-m}, \ldots. X_{tn-m}$ for all $t_1, t_2, \ldots t_n$ are the same and lag m which is the time difference.

In this case, $E(X_t)=E(X_{t-m})$, $Var(X_t)=Var(X_{t-m})$ for all t and m, and $Cov(X_t, X_r)=Cov(X_{t-m}, X_{r-m})$ for all values of $t$,$m$ and $r$.

Consider an observed series $X_1, X_2, X_3, \ldots X_t$. We can form *n-1* pairs of observations, for instance; $(X_1, X_2), (X_2, X_3) \ldots (X_{n-1}, X_n)$ where each pair of observations is separated by a one-time interval. Taking the observations in each pair as separate variables, we can compute the autocorrelation between $X_1$ and $X_{t+1}$ as:

$$S_m = \frac{\sum_{t=1}^{n-m}(X_t - \overline{X)(X_{t+m} - \bar{X}})}{\sum_{t=1}^{n}(X_t - \bar{X})^2} \tag{1}$$

Thus, $S_m$ is the **autocorrelation coefficient at lag m.** A plot of $S_m$ against lag m for m = 0, 1, 2 ... and k < n is called **sample Autocorrelation Function (ACF).**

Testing for partial correlation in a stationary time series can also be done. **Partial Autocorrelation** is the correlation between $X_1$ and $X_{t-1}$ after removing the effect of the intervening variables $X_{t-1}, X_{t-2}, X_{t-3}, \ldots X_{t-m+1}$. It is usually called the **Partial Autocorrelation Function (PACF) at lag m** and if denoted by $\phi_{mm}$ and it can be defined as $\phi_{mm} = corr(X_t, X_{t-m} \,|\, X_{t-1}, X_{t-2}, X_{t-3}, \ldots, X_{t-m+1})$

Thus, $\phi_{mm}$ measures the correlation between $X_t$ and $X_{t-m}$ given $X_{t-1}, X_{t-2}, X_{t-3}, \ldots X_{t-m+1}$ or the correlation between $X_t$ and $X_{t-m}$ after adjusting for the effects of $X_{t-1}, X_{t-2}, X_{t-3}, \ldots X_{t-m+1}$.

Stationarity can be achieved if the pattern caused by the time-dependent autocorrelation is removed. Lastly, in comparing models, the best model should have the smallest standard error, Akaike's Information Criterion (AIC), and Bayesian Information Criterion (BIC) values.

### 3.2. The Intervention Analysis Methods

According to Box, Jenkins, and Reinsel (2008), time series are time and again affected by measures, happenings or circumstances, such as strikes, economic shocks, policy changes, environmental regulations, and similar occurrences, which we shall refer to as intervention events. Intervention analysis is used to access the magnitude of impact that these various intervention mechanisms have on a time series data. A stochastic, time-series ARIMA (p,d,q) model will help in analyzing the dynamics of changes, discrepancies, and disruptions in the VAT Revenue through time-series data. The core emphasis is to approximate the vibrant influence of the increase in the VAT rate by 2.5% in January 2014 as an intervention mechanism on VAT Revenues collected. In building up a time-series intervention analysis, we make an initial assumption that an intervention event had occurred at timeTof the time series. This intervention analysis will help us access the exact impact of a known intervention on a time series data. It is of concern to determine whether there is any signal of change connected with this known intervention on the time series under the associated intervention mechanism.

### 3.3. Transfer Function and Univariate ARIMA Model

Transfer function denotes the process of accounting for the dynamic association between two-time series $Y_t$ and $X_t$ (where the latter represents the input series whiles the former represents the output series) where previous values of both series may be used in predicting $Y_t$, resulting in a substantial decreasing in the errors of the prediction. The overall transfer function of an ARIMA is of the form:

$$Y_t = \sum\left[\omega(B)/\delta(B)\right]B^b X_t + \left[\theta(B)/\varnothing(B)\right]\grave{o}_t \tag{2}$$

where $Y_t$ and $X_t$ denote both the output and input series respectively, $b$ denotes the delay time for the impact of the intervention to occur, $\omega(B)/\delta(B)$ is the polynomial of the transfer function, $[\theta(B)/\emptyset(B)]$ denotes the noise model, and $\grave{O}_t$ is the residual or simply the white noise. The equation above can furthermore be simplified as

$$Y_t = V(B)X_t + N_t \tag{3}$$

Where

$$V(B) = \delta^{-1}(B)\omega(B)B^b$$
$$\omega(B) = \omega_0 + \omega_1 B + \ldots + \omega_s B^s$$
$$\delta(B) = 1 - \delta_1 B - \ldots - \delta_r B^r \quad \text{and}$$
$$N_t = \left[\theta(B)/\varnothing(B)\right]\grave{o}_t$$

### 3.4. Transfer Function and Univariate ARIMA Model

According to Box and Tiao (1975), the general form of an intervention model is denoted by

$$Y_t = V(B)I_t + N_t \tag{4}$$

Where *V(B)* denotes the transfer function, $I_t$ is an intervention indicator of deterministic input series and $N_t$ is a noise model.

The impact of intervention has two forms of deterministic input series which have been established to be very beneficial in intervention analysis. The occurrence of a known intervention is denoted as 1 at time $t = T$ and as such in the case where the deterministic input series is a pulse function (when the known intervention occurs at a single index of time) and stays the same as 1 in the case of a step function (when the known intervention continuously occurs beginning with a time index denoted say $t_0$).

Mathematically, the deterministic input series of an intervention analysis in terms of the pulse function is given as

$$P_t^{(T)} = \begin{cases} 0 & t \neq T \\ 1 & t = T \end{cases}$$

While the step function is also denoted as

$$S_t^{(T)} = \begin{cases} 0 & t < T \\ 1 & t \geq T \end{cases}$$

Which represent the influence of identified interventions that are likely to continue permanently after time *T* to some point. In this instance the intervention input begins in 2014 *(t=T)* where *t* is coded as 1, and remains for just a period in the case of the pulse function, but remains as 1 for the entire presence of the intervention exercise in the case of the step function and is, therefore, concerning the increase in VAT rate intervention event is formulated as;

$$Y_t = c + \omega_1 I_{1t} + \frac{\theta(B)}{\varnothing(B)} \in_t \qquad \text{where} \qquad I_{1t} = S_t^{(2014)} = \begin{cases} 1 & t \geq 2014 \\ 0 & Otherwise \end{cases}$$

Here the *c* is a constant and *Y* is the level of variation concerning gains or losses made in the value of reduction. The intervention variable in this study is a step function that relates to the increase in VAT rate intervention.

### 3.5. Choosing the best trend model

Pegels (1969) proposed taxonomy for choosing the best modelling framework for a given data. This taxonomy was extended by Gardener (1998), also extended by Makridakis, Wheelwright, and Hyndman (1998) and further modified by Hyndman et al (2002). The modified taxonomy by Hyndman et al

(2002) is adopted in this study as a guide for selecting among the trend forecasting models. The taxonomy is shown in Table 1.

**Table 1.** Taxonomy for selecting trend forecasting model

| TREND COMPONENT | SEASONAL COMPONENT | | |
|---|---|---|---|
| | **N** | **A** | **M** |
| *N* | NN (simple exponential smoothing) | NA | NM |
| *A* | AN (Holt linear) | AA (Additive Holt-Winters) | AM (multiplicative holt winters) |
| *M* | MN | MA | MM |
| *D* | DN | DA | DM |

**Note:** N is None; A is Additive; M is Multiplicative, D is Damped.
**Source:** Hyndman et al (2002)

From Table 1 above, considering the case in cell NN, a simple exponential smoothing method is to be employed for modelling and forecasting. Holt's linear method is to be employed for the case in cell AN. Again, for the case in cell AA, the Additive Holt-Winters method is to be employed and Multiplicative Holt-Winters method for the case of AM for modelling and forecasting. Less commonly used modelling and forecasting methods are employed for the cases in the other cells. The Holt linear method is the preferred trend model for this study because the VAT Revenue data is additive and non-seasonal.

### 3.6. Holt's linear trend method

Simple exponential smoothing was augmented by Holt (1957) to facilitate the forecasting of data with a trend. This method of forecasting involves the following equations: Forecast equation and two smoothing equations (Level equation and trend equation) as shown below:

Forecast equation; $$\hat{x}_{t+h|t} = \ell_t + hb_t \tag{5}$$

Level equation; $$\ell_t = \alpha x_t + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{6}$$

Trend equation; $$b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1} \tag{7}$$

Where $\ell_t$ represents an estimate of the level of the data series at time *t*; $b_t$ represents an estimate of the trend (which can also be called the slope) of the data series at time $t$; $\alpha$ denotes the smoothing parameter for the level, $0 \leq \alpha \leq 1$ and $\beta$ denotes the smoothing parameter for the trend $0 \leq \beta \leq 1$.

The level equation of the Holt linear trend indicates that for the within-sample one-step-ahead forecast for $t$, which is given by $\ell_{t-1} + b_{t-1}$ with $\gamma_t$ as observation; $\ell_t$ is a weighted average. Also, based on $\ell_t - \ell_{t-1}$ and $b_{t-1}$ (which is the previous estimate of the trend); $b_t$ is a weighted average of the estimated trend at time $t$. The forecast function thus is trending and no longer flat. It is also worth noting that $h$ times the last estimated trend value plus the last estimated level is equal to the $h$-h-step-ahead forecast, thus the forecasts will have a linear function.

### 3.7. Measures of Accuracy in Prediction

A frequently used measure of the accuracy of predictions is Root Mean Square Error (RMSE) and Mean Absolute Deviation (MAD). The smaller is RMSE and MAD, the better the forecasting model in precision and vice versa.

### 3.8. Data Sources

The data for the analysis is sourced from the Ministry of Finance revenue targets to the tax agencies and the Ghana Revenue Authority's revenue forecasts.

## 4. Results and Discussion

### 4.1. Exploration of Data

This section of the study explores the trend in the series and assesses the stationarity of the series through the ADF unit root test. Figure 1 presents the time series plot of the VAT revenue recorded.

From Figure 1, VAT revenue in the country has been on the rise throughout the entire study period. Between the years of 2002 and 2010, increases in VAT revenue has been very steady. However, there was an unusual increase in Domestic VAT Revenue in December 2008. This may be as a result of the introduction of the 3% VAT Flat rate in September 2007. From 2011 to 2017, both domestic and import VAT revenue experienced several fluctuations while increasing. From the observed patterns in Figure 1, it is seen clearly that the Total VAT Revenue, Domestic VAT Revenue, and Import VAT Revenue all have an increasing trend thus all likely to be nonstationary. The stationarity in the series is further explored by an ADF unit root test shown in Table 2 below.

**Figure 1.** Times Series Plot of Total VAT, Domestic VAT, Import VAT Revenue Data

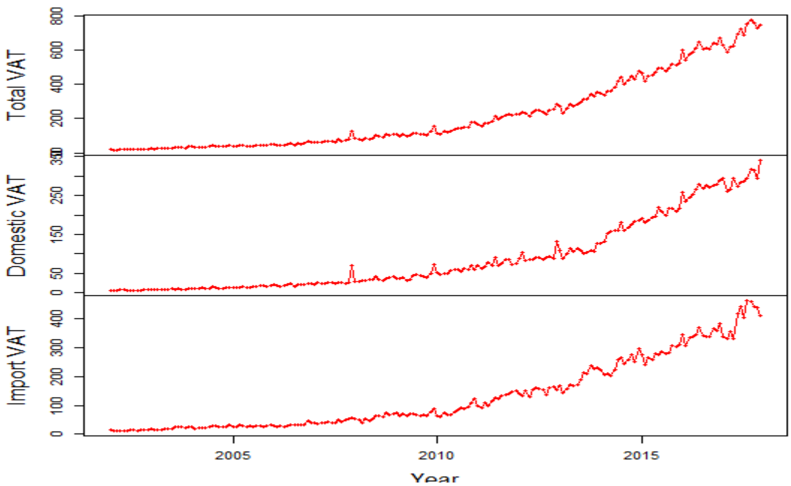



**Table 2.** ADF Unit root test for VAT Revenue Data

| Variable | Level | | $1^{st}$ Difference | |
|---|---|---|---|---|
| | *t-statistic* | *P – value* | *t-statistic* | *P – value* |
| ***Total VAT*** | 1.3061 | 1.0000 | -6.4000 | 0.0000 |
| ***Domestic VAT*** | 3.5714 | 1.0000 | -5.3852 | 0.0001 |
| ***Import VAT*** | -1.3136 | 0.8815 | -9.6805 | 0.0000 |

The null hypothesis of a unit root (that is integrated of order one, I(1) was tested with the ADF unit root test in both the non-differenced (level) and the differenced series. All series were non-stationary at the level (p-values > 0.05). After first difference, all series were stationary (p-values < 0.05). Figure A1 in Appendix A presents the plot of the first-differenced series. After differencing the series once, the data appears to be stationary concerning mean. However, there was high volatility (Figure A1). The Phillips-Perron unit root test was also employed to corroborate the result of the ADF unit root test. Since both unit root tests reveal non-stationarity at the level (p-vaules > 0.05) and stationarity at first difference as indicated in Table A1 (Appendix A), we can therefore indisputably conclude that the series is I(1).

### 4.2. The Intervention Time Series Modelling

In this section of the study, the effect of the intervention (increase in VAT standard rate from 12.5% to 15% which took effect from January 2014) on the series is assessed. The pre-intervention ARIMA model was fitted. Besides, the ARIMA model with the intervention effect was modeled. The pre-intervention period spans from the year 2002 to 2013. Thus, the pre-intervention model was developed with monthly VAT (Total VAT, Domestic VAT, and Import VAT) data from 2002 to 2013.

Tables A2 and A3 (Appendix A) present the ADF and Phillips-Perron unit root test of the pre-intervention series. It was observed that the pre-intervention series is I(1). All series were non-stationary at the levels but stationary after the first difference.

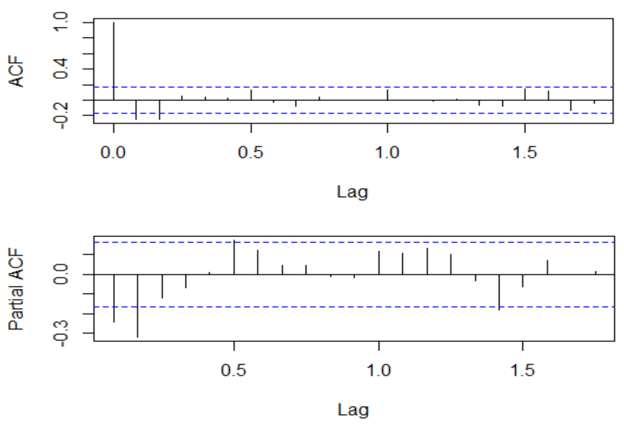
### 4.3. Fitting an ARIMA Model for the Pre-Intervention Time Series Data

The ARIMA model for the pre-intervention model as well as the intervention time series model was estimated for Total, Domestic, and Import VAT in this section. The intervention effect was assessed, and the forecast made.

#### Total VAT Revenue

The plot of ACF and PACF of the First Differenced Total VAT data is depicted in Figure 2 below.

**Figure 1.** Correlogram (ACF & PACF) First Differenced Pre-Intervention Total VAT Revenue Series



From Figure 2, it can be observed that two positive spikes cut off after lag 2 as depicted by the PACF graph. However, the graph had other significant spikes at the other lags. It suffices that we may have a moving average with two periods. Furthermore, its ACF is in sinusoidal waves and it gradually tails off. Based on the significant lags of both the ACF and PACF, tentative models were identified for the Total VAT (Table 3).

**Table 3.** Tentative ARIMA Models for Pre-Intervention Total VAT Series

| Model | AIC | AICc | BIC |
|---|---|---|---|
| ARIMA(1, 1, 1) | 1133.35 | 1133.53 | 1142.24 |
| ARIMA(0, 1, 1) | 1132.28 | 1132.37 | 1138.21 |
| ARIMA(1, 1, 0) | 1136.62 | 1136.70 | 1142.54 |
| **ARIMA(2, 1, 0)*** | **1129.11*** | **1129.28*** | **1138.00*** |
| ARIMA(0, 1, 2) | 1132.17 | 1132.34 | 1141.06 |
| ARIMA(2, 1, 1) | 1131.03 | 1131.32 | 1142.88 |

**Note:** * means best, based on the selection criteria

From Table 3, using the values of AIC, AICc, and BIC, the model was the most appropriate model that projects the pre-intervention Total VAT revenue. The parameters of the model were then estimated and presented in Table 4.

**Table 4.** Estimates of Parameters for ARIMA(2, 1, 0) Model

| Variable | Coefficient | Standard Error | t-statistic | p-value |
|---|---|---|---|---|
| $\alpha_1$ | -0.2586 | 0.0816 | -3.17 | 0.0019 |
| $\alpha_2$ | -0.2552 | 0.0813 | -3.14 | 0.0021 |

Recalling the general form of the ARIMA model,

$$\alpha(B)(1-B)^d x_t = \beta(B)z_t$$

From Table 3, the ARIMA model for Total VAT is given by

$$\left(1-\alpha_1 B-\alpha_2 B^2\right)\left(1-B\right)x_t = z_t$$

$$\left(1+0.2586_1 B+0.2552B^2\right)\left(1-B\right)x_t = z_t$$

The goodness of fit of the model was assessed through the plot of the residuals, its ACF as well as PACF. Also, the Ljung-Box test (test of autocorrelation) and ARCH-LM test (test of heteroscedasticity) was performed. These are presented in Appendix A; Figure A2, Table A4, and Table A5. The plot of residual indicated a high level of volatility in the series. However, the plot of the ACF and PACF indicated that much variability was accounted for by the model. The Ljung-Box test indicated the absence of autocorrelation. However, the ARCH-LM test confirmed the presence of volatility in the data. It can be concluded that the model *ARIMA(2, 1, 0)* provides an adequate representation of the pre-intervention Total VAT revenue.

The effect of the intervention was further explored and presented in Table 5.

**Table 5.** Parameter Estimates for Intervention Model for Total VAT

| Variable | Coefficient | Standard Error | Z value | p–value |
|---|---|---|---|---|
| $\alpha_1$ | -0.2383 | 0.0714 | -3.3382 | 0.0008 |
| $\alpha_2$ | -0.1690 | 0.0716 | -2.3619 | 0.0182 |
| *T1-AR1 (δ)* | 0.0747 | 1.2565 | 0.0595 | 0.9526 |
| *T1-MA0 (ω)* | -2.9138 | 17.7435 | -0.1642 | 0.8696 |

From Table 4 above, the various parameter estimates for the full intervention model with their respective coefficients, standard errors, and z-values are shown. The coefficients for *AR1* ($\alpha_1$) and *AR2* ($\alpha_2$) are significant (p-value < 0.05). However, *T1-AR1* and *T1-MA0* which represent both the decay or reduction parameter, and the impact parameter had coefficients of 0.0747 and -2.9138 respectively which were statistically insignificant (p-value > 0.05). This implies that the 2.5% increase in the standard VAT rate in January 2014 did not trigger a significant effect on Total VAT Revenue. The insignificant response of Total VAT Revenue to increase in the VAT rate agrees with the studies of Nartey (2011) and Antwiet al (2012) which also revealed an insignificant response of Total VAT Revenue to increase in the VAT rate. However, it contradicts the studies of Narayan (2003), Slobodnitsky and Drucker (2008), and Charletand Jeffrey (2010) which concluded that an increase in VAT rates results in a significant increase in tax revenue and hence government revenue.

The plot of both the observed and fitted total VAT using the time series intervention model is presented in Figure A3 while the fitted values for 2017 are presented in Table A10 (all in Appendix A). It is observed that the fitted values follow the pattern of the observed values indicating goodness of fit.

**Domestic VAT Revenue**

The plot of ACF and PACF of the first-differenced Domestic VAT data is presented in Figure A4 in Appendix A. Based on the significant lags of both the ACF and PACF, tentative models were identified for the Domestic VAT (Table 6).

**Table 6.** Tentative ARIMA Models for Pre-Intervention Domestic VAT Series

| Model | AIC | AICc | BIC |
|---|---|---|---|
| ARIMA(3, 1, 0) | 992.34 | 992.63 | 1004.19 |
| ARIMA(3, 1, 1) | 990.10 | 990.53 | 1004.91 |
| ARIMA(0, 1, 3) | 985.02 | 985.31 | 996.87 |
| ARIMA(1, 1, 3) | 979.03 | 979.47 | 993.84 |
| ARIMA(4, 1, 0) | 989.36 | 989.80 | 1004.18 |
| ARIMA(4, 1, 1) | 990.67 | 991.29 | 1008.45 |
| ARIMA(0, 1, 4) | 982.86 | 983.30 | 997.68 |
| **ARIMA(1, 1, 4)*** | **967.13*** | **967.74*** | **984.90*** |

**Note:** * means best, based on the selection criteria

From Table 6, using the values of AIC, AICc and BIC, the model *ARIMA(1, 1, 4)* was the most appropriate model that projects the pre-intervention Domestic VAT revenue. The parameters of the model *ARIMA(1, 1, 4)* were then estimated and presented in Table 7.

**Table 7.** Estimates of Parameters for ARIMA(1, 1, 4) Model

| Variable | Coefficient | Standard Error | t-statistic | p-value |
|---|---|---|---|---|
| $\alpha_1$ | 0.9956 | 0.0063 | 164.49 | 0.0000 |
| $\beta_1$ | -1.8240 | 0.0836 | -21.83 | 0.0000 |
| $\beta_2$ | 0.5956 | 0.1648 | 3.61 | 0.0000 |
| $\beta_3$ | 0.4387 | 0.1601 | 2.75 | 0.0068 |
| $\beta_4$ | -0.1978 | 0.0806 | -2.45 | 0.0154 |

Recalling the general form of the ARIMA model,

$$\alpha(B)(1-B)^d x_t = \beta(B) z_t$$

From Table 6, the ARIMA model for Domestic VAT is given by

$$(1-\alpha_1 B)(1-B)x_t = (1+\beta_1 B+\beta_2 B^2+\beta_3 B^3+\beta_4 B^4)z_t$$
$$(1-0.9956B)(1-B)x_t = (1-1.8240B+0.5956B^2+0.4387B^3-0.1978B^4)z_t$$

Here also, the goodness of fit of the model was assessed through the plot of the residuals, its ACF as well as PACF. This is presented in Figure A4, Appendix A. Also, theLjung-Box test (test of autocorrelation) and ARCH-LM test (test of heteroscedasticity) was performed and are presented in Tables A6 and A7, Appendix A. The plot of residual indicated a high level of volatility in the series. This was confirmed by the ARCH-LM test. The plot of the ACF and PACF indicated that much variability was accounted for by the model. Besides, the Ljung-Box test indicated the absence of autocorrelation. However, the ARCH-LM test confirmed the presence of volatility in the data. It can be concluded that the model *ARIMA(1, 1, 4)* provides an adequate representation of the pre-intervention Domestic VAT revenue. The effect of the intervention was further explored and presented in Table 8.

**Table 8.** Parameter Estimates for Intervention Model for Domestic VAT

| Variable | Coefficient | Standard Error | t-statistic | p-value |
|---|---|---|---|---|
| $\alpha_1$ | -0.2455 | 0.7721 | -0.318 | 0.7505 |
| $\beta_1$ | -0.3165 | 0.8117 | -0.3899 | 0.6966 |
| $\beta_2$ | -0.2951 | 0.4597 | -0.6421 | 0.5208 |
| $\beta_3$ | 0.2293 | 0.1121 | 2.0458 | 0.0408 |
| $\beta_4$ | 0.1588 | 0.2314 | 0.6861 | 0.4926 |
| T1-AR1 ($\delta$) | 0.9635 | 0.0073 | 131.7026 | 0.0000 |
| T1-MA0 ($\omega$) | 8.0243 | 2.1056 | 3.8109 | 0.0001 |

From Table 8 above, the various parameter estimates for the full intervention model with their respective coefficients, standard errors, and z-values are shown.

The coefficients for AR1 ($\alpha_1$), MA1 ($\beta_1$), MA2 ($\beta_2$), and ($\beta_4$) are insignificant (p-value > 0.05). However, MA3 ($\beta_3$) is significant. Besides, TI-AR1 and T1-MA0 have coefficients of 0.9635 and 8.0243 respectively which are statistically significant (p-value < 0.05). This implies that the 2.5% increase in the standard VAT rate in January 2014 triggered a positive effect (increase in Domestic VAT Revenue) of magnitude 8.0243 since the decay parameter has a positive coefficient (0.9635). Domestic VAT Revenue increased steadily in February 2014 and has had an increasing trend to date. The steady increase in Domestic VAT Revenue can, therefore, be attributed to the intervention (i.e. the 2.5% increase in VAT rate) in January 2014. The significant positive response of Domestic VAT Revenue to increase in the VAT rate may be further attributed to the efficiency in tax administration which has reduced VAT avoidance and evasion, increased tax compliance, broadened the Domestic VAT base in Ghana, and lessoned corruption. This agrees with the studies of Jack (1996), Gebaueret al. (2007), Bird and Gendron (2007), De Mello (2009), and Keen (2013) which all corroborate that efficiency in tax administration will always result in tax revenue growth.

The significant response of Domestic VAT Revenue to increase in the VAT rate agrees with Narayan (2003), Slobodnitsky and Drucker (2008), and Charletand Jeffrey(2010) who concluded that increase in VAT rates results in a significant increase in tax revenue and hence government revenue.

The plot of both the observed and fitted domestic VAT using the time series intervention model is presented in Figure A5 while the fitted values for 2017 are presented in Table A10 (all in Appendix A). The fitted values follow the pattern of the observed values indicating goodness of fit.

### Import VAT

The plot of ACF and PACF of the First differenced Import VAT data is presented in Figure A6 in Appendix A.Based on the significant lags of both the ACF and PACF, tentative models were identified for the Import VAT (Table 9).

**Table 9.** Tentative ARIMA Models for Import VAT Series

| Model | AIC | AICc | BIC |
|---|---|---|---|
| ARIMA(1, 1, 1) | 1017.02 | 1017.19 | 1025.90 |
| ARIMA(0, 1, 1) | 1015.13 | 1015.21 | 1021.05 |
| ARIMA(1, 1, 0) | 1015.82 | 1015.91 | 1021.75 |
| ARIMA(2, 1, 0) | 1015.97 | 1016.14 | 1024.86 |
| ARIMA(0, 1, 2) | 1016.85 | 1017.02 | 1025.74 |
| **ARIMA(2, 1, 1)*** | **1013.56*** | **1013.85*** | **1025.41*** |

**Note:** * means best, based on the selection criteria

From Table 9, using the values of AIC, AICc, and BIC, the model *ARIMA(2, 1, 1)* was the most appropriate model that projects the pre-intervention Import VAT revenue. The parameters of the model *ARIMA(2, 1, 1)* were then estimated and presented in Table 10.

**Table 10.** Estimates of Parameters for ARIMA(2, 1, 1) Model

| Variable | Coefficient | Standard Error | t-statistic | p-value |
|---|---|---|---|---|
| $\alpha_1$ | -1.0115 | 0.1933 | -5.23 | 0.0000 |
| $\alpha_2$ | -0.3246 | 0.0808 | -4.02 | 0.0000 |
| $\beta_1$ | 0.7640 | 0.1959 | 3.89 | 0.0000 |

Recalling the general form of the ARIMA model,

$$\alpha(B)(1-B)^d x_t = \beta(B)z_t$$

From Table 9, the ARIMA model for Import VAT is given by

$$\left(1-\alpha_1 B-\alpha_2 B^2\right)\left(1-B\right)x_t = (1+\beta_1 B)z_t$$
$$\left(1+1.0115B+0.3246B^2\right)\left(1-B\right)x_t = (1+0.7640B)z_t$$

Furthermore, the goodness of fit of the model was assessed through the plot of the residuals, its ACF as well as PACF. This is presented in Figure A6, Appendix A. Also, the Ljung-Box test (test of autocorrelation) and ARCH-LM test (test of heteroscedasticity) was performed and are presented in Tables A8 and A9, Appendix A. The plot of residual indicated a high level of volatility in the series. This was confirmed by the ARCH-LM test. The plot of the ACF and PACF indicated that much variability was accounted for by the model. Also, the Ljung-Box test indicated the absence of autocorrelation. However, the ARCH-LM test confirmed the presence of volatility in the data. It can be concluded that the model *ARIMA(2, 1, 1)* provides an adequate representation of the pre-intervention Import VAT revenue. The effect of the intervention on Import VAT was further explored and presented in Table 11.

From Table 11 below, the various parameter estimates for the full intervention model with their respective coefficients, standard errors, and z-values are shown. The coefficients for AR1 ($\alpha_1$), AR2 ($\alpha_2$), and MA1 ($\beta_1$) are significant (p-value < 0.05). However, TI-AR1 and T1-MA0 had coefficients of 0.2819 and, -16.008 respectively which were statistically insignificant (p-value > 0.05). This implies that the 2.5% increase in the standard VAT rate in January 2014 did not trigger a significant effect on Import VAT Revenue. The insignificant positive response of Import VAT Revenue to increase in the VAT rate may be attributed to inefficiencies in VAT administration which may include corrupt practices between importers and customs officers in Ghana. This agrees with the findings of Bird et al (2008) and Sokolovska (2015) who stated that high levels of corruption slow down tax revenue growth. Igbinosa (2016), also realizing from his study that Customs Excise Tax was negatively related to GDP, attributed the aberrant result to smuggling and corrupt practices by importers and customs officers.

**Table 11.** Parameter Estimates for Intervention Model for Import VAT

| Variable | Coefficient | Standard Error | t-statistic | p-value |
|---|---|---|---|---|
| $\alpha_1$ | -1.1126 | 0.0845 | -13.1722 | 0.0000 |
| $\alpha_2$ | -0.4336 | 0.0672 | -6.4542 | 0.0000 |
| $\beta_1$ | 0.8650 | 0.0730 | 11.845 | 0.0000 |
| T1-AR1 ($\delta$) | 0.2819 | 0.3455 | 0.8159 | 0.4146 |
| T1-MA0 ($\omega$) | -16.0080 | 11.4120 | -1.4027 | 0.1607 |

The insignificant response of Import VAT Revenue to increase in the VAT rate agrees with the studies of Nartey (2011) and Antwiet al (2012) which also revealed an insignificant response of Import VAT Revenue to increase in the VAT rate. However, it contradicts the studies of Narayan (2003), Slobodnitsky and Drucker (2008), and Charletand Jeffrey(2010) which concluded that an increase in VAT rates results in a significant increase in tax revenue and hence government revenue. Also, though not many imports are exempt and zero-rated from VAT, there was not a significant change in Import VAT Revenue because the very valuable imported plant, machinery, and equipment used in industries are exempted from Import VAT in Ghana according to the provisions of the VAT amendment Act 948, 2017.

The plot of both the observed and fitted domestic VAT using the ARIMA with intervention model is presented in Figure A7 while the fitted values for 2017 are presented in Table A10 (all in Appendix A). It is observed that the fitted values follow the pattern of the observed values indicating goodness of fit.

### 4.4. Trend Analysis

The VAT revenue data (Total VAT, Domestic VAT, and Import VAT) exhibits an increasing rise and fall trend, however, it is not seasonal. Thus, in choosing the trend model for forecasting and considering the features of the data, it was very necessary to explore beyond the linear trend, logarithmic trend, polynomial trend, power trend, and the exponential trend models. Referring to the taxonomy in Table 1 since the VAT revenue data (Total VAT, Domestic VAT, and Import VAT) is additive but non-seasonal, the best modelling and forecasting method for this research is the Holt linear trend method.

**Holt Linear Trend Model**

The increasing trend in the series is modeled using the Holt linear trend method. The trend model for Total VAT, Import VAT, and Domestic VAT was fitted. The plots of the original series (black) and the fitted series (red) using the Holt linear trend method are presented in Figure B1 in Appendix B.It is observed that the fitted values follow the pattern of the observed values indicating goodness of fit. The estimate of the parameters for fitting Holt linear trend equations, that is the forecast equation and the two smoothing equations (i.e. the level equation and the trend equation) are presented in Table 12. Here, $\ell_t$ denotes an estimate of the level of the series at time t. $b_t$ also denotes the estimate of the trend (slope) of the series at time t. For the smoothing parameters of the level and trend, $\alpha$ denotes the smoothing parameter for the level while $\beta$ denotes the smoothing parameter for the trend.

**Table 12.** Estimate of Holt's linear trend Parameters

| | Total VAT | Domestic VAT | Import VAT |
|---|---|---|---|
| **Smoothing Parameters** | | | |
| Alpha ($\alpha$) | 0.4813 | 0.3601 | 0.5847 |
| Beta ($\beta$) | 0.0527 | 0.5841 | 0.0351 |
| **Coefficients** | | | |
| Level ($\ell_t$) | 756.5771 | 320.1854 | 427.2283 |
| Slope ($b_t$) | 8.6874 | 3.79795 | 4.22997 |

From Table 12, the trend equation, level equation, and forecast equation for total, domestic, and import VAT are deduced as follows;

*Trend Equation:* $b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1}$

*Level Equation:* $\ell_t = \alpha x_t + (1-\alpha)(\ell_{t-1} + b_{t-1})$

*Forecast Equation:* $\hat{x}_{t+h|t} = \ell_t + hb_t$

From Table 12, the weighted average of the observed Total, Domestic, and Import VAT Revenues are respectively 756.5771, 320.1854, and 427.2283. Also, the weighted average of the estimated trend for total, domestic, and import VAT are 8.6874, 3.798, and 4.22997 respectively. Forecasts for total, domestic, and import VAT recorded in 2017 were obtained and are presented in Table B1, Appendix B.

### 4.5. Cross-Validation of Intervention ARIMA & Holt Linear Trend Model

From the 2017 forecast using the ARIMA model with Intervention effect and Holt linear trend analysis, both models predicted with a small margin of error. On average, the forecast by ARIMA model with Intervention effect was below what was observed values in 2017 whiles that of Holt's linear trend technique exceeded observed values in 2017. As both the Holt linear trend model and the ARIMA with intervention analysis model were used to predict the monthly VAT (Total VAT, Domestic VAT, and Import VAT) revenues in 2017, the RMSE, MAPE, and MAD were used to compare the precision in prediction of both models. The RMSE, MAPE, and MAD were computed using the predicted values and the observed values in 2017 for both models.

It was observed that ARIMA with intervention analysis model had a lesser RMSE, MAPE, and MAD for the predicted values of Total VAT Revenue, Domestic VAT Revenue, and Import VAT Revenue. As shown in Appendix A table A10, using the ARIMA with intervention analysis model to predict VAT revenues in 2017, the RMSE for Total VAT Revenue, Domestic VAT Revenue, and Import VAT Revenue was 37.22, 17.02 and 32.20 respectively whiles the MAD for Total VAT Revenue, Domestic VAT Revenue and Import VAT Revenue was 30.25, 14.80 and 24.41 respectively and the MAPE for Total VAT Revenue, Domestic VAT Revenue, and Import VAT Revenue was 4.37, 5.01 and 5.97 respectively as shown in Appendix A table A10. Using the Holt linear trend model, on the other hand, to predict VAT Revenues in 2017, the RMSE for Total VAT Revenue, Domestic VAT Revenue, and Import VAT Revenue is 43.65, 27.83 and 37.70 respectively whiles the MAD for Total VAT Revenue, Domestic VAT Revenue and Import VAT Revenue was 35.70, 24.05 and 33.82 respectively and the MAPE for Total VAT Revenue, Domestic VAT Revenue, and Import VAT Revenue was 5.45, 8.49 and 8.74 respectively as shown in Appendix B Table B1.This result thus agrees with the studies of Favero and Marcellino

(2005) and Nazmi and Leuthold (1988) that found that ARIMA outperforms other models in forecast precision in the short run.

### 4.6. Comparison of In-house and ARIMA with Intervention Forecast Figures

Since ARIMA with intervention model outperformed the Holt linear trend model, ARIMA with intervention model was further compared with the in-house model of GRA. The RMSE, MAPE, and MAD were again used to compare the precision in prediction of forecast figures produced by the ARIMA with intervention model and the GRA target figures for the period, 2017 to 2019 (36 months).

It was observed that the RMSE, MAPE, and MAD for the predicted values of Total VAT Revenue using the ARIMA with intervention model were less than RMSE, MAPE, and MAD for the GRA target figures. Moreover, for Domestic VAT revenue only, the MAD and RMSE of the GRA target figures were lesser than the predicted figures of the ARIMA with intervention model but otherwise for MAPE. Also for the Import VAT revenue only, the MAD and MAPE of the predicted figures of the ARIMA with intervention model were less than of the GRA target but otherwise for the RMSE (These are shown in Table C1 of Appendix C).

## 6. Conclusion and Policy Suggestions

Results from the analysis prove that ARIMA with intervention analysis model is a better forecasting approach than the Holt Linear Trend model because it gives a more accurate prediction of Ghana's monthly Total VAT revenue, Domestic VAT Revenue, and, Import VAT Revenue.

Also, it was realized that the increase in the standard VAT rate in January 2014 by 2.5% did not have a significant effect on Total VAT revenue though some significant effect was realized in the Domestic VAT revenues that were collected from February 2014 to date. The overall insignificant response of Total VAT revenue to the change in the VAT rate may be as a result of revenue leakages in the VAT system. We thus submit that increasing the VAT rate without sealing the VAT revenue leakages is likely to result in an insignificant response of VAT revenue to the change in the VAT rate. We recommend that the effect of interventions (e.g. discretionary VAT policy change) should be analyzed using the ARIMA with intervention for accurate forecasting of monthly VAT revenue by the Ghana Revenue Authority.

In addition, the ARIMA with intervention model is more precise in predicting the VAT figure than the in-house model adopted by the Ghana Revenue Authority in forecasting monthly VAT revenues which are used for budgetary policies of the government. We thus recommend the ARIMA method for the GRA on grounds of precision and effective fiscal planning.

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**APPENDIX-A**

**Figure A1:** Times Series Plot of First Difference of Total VAT, Domestic VAT, and Import VAT Revenue Data

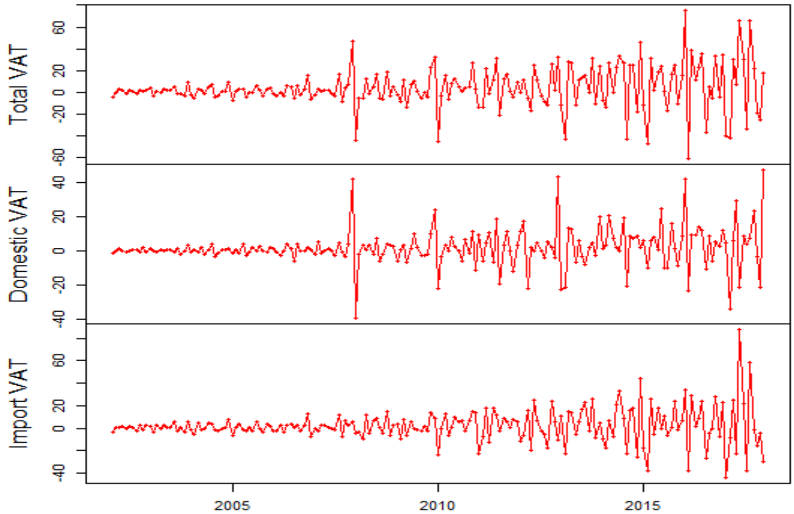


**Figure A2:** Plot of Residual Diagnostics for ARIMA(2, 1, 0) Model

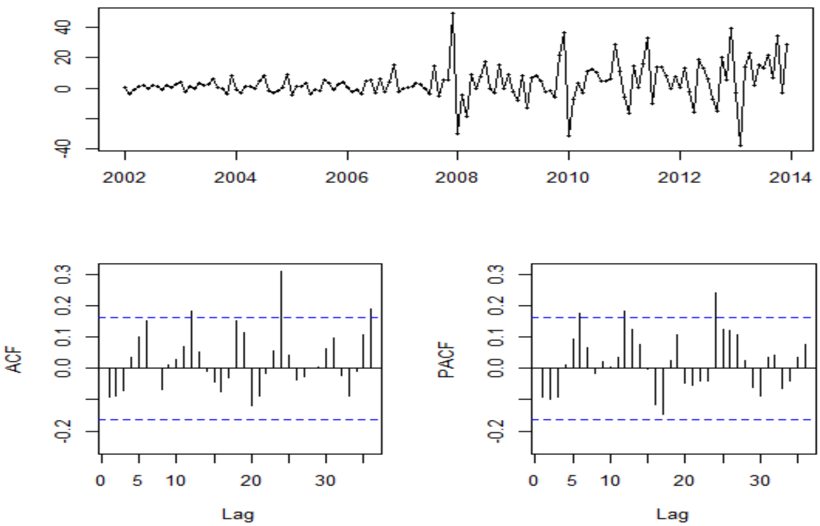

**Figure A3:** Plot of Observed and Fitted Total VAT Revenue from Intervention Model

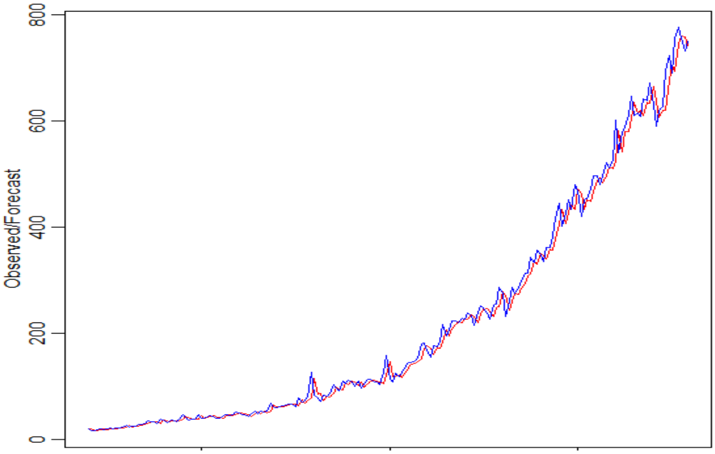


**Figure A4:** Correlogram (ACF and PACF) First Differenced Pre-Intervention Domestic VAT Revenue Series

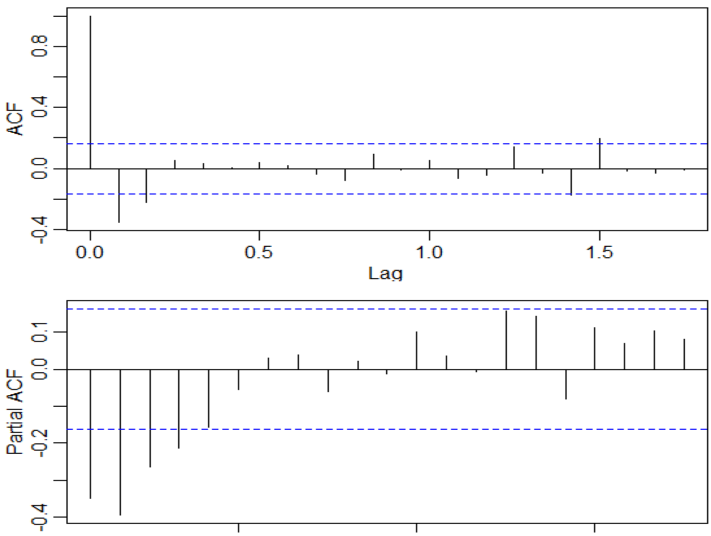

**Figure A5:** Plot of Observed and Fitted Domestic VAT revenue from intervention model

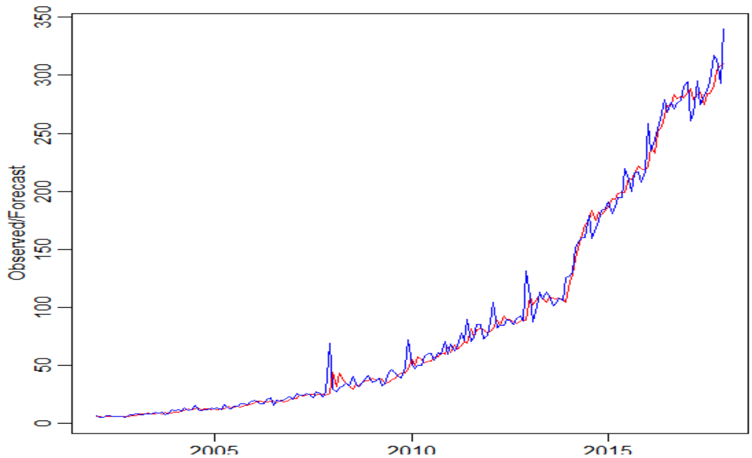


**Figure A6:** Correlogram (ACF and PACF) first differenced Import VAT

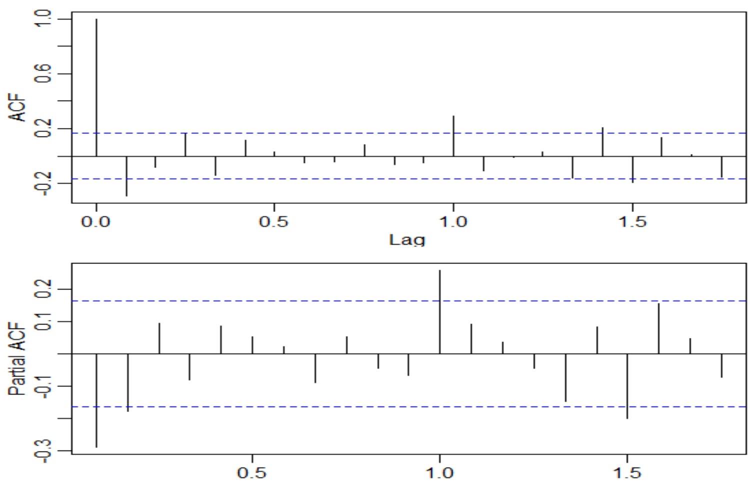

**Figure A7:** Plot of Observed and Fitted Import VAT Revenue from Intervention Model

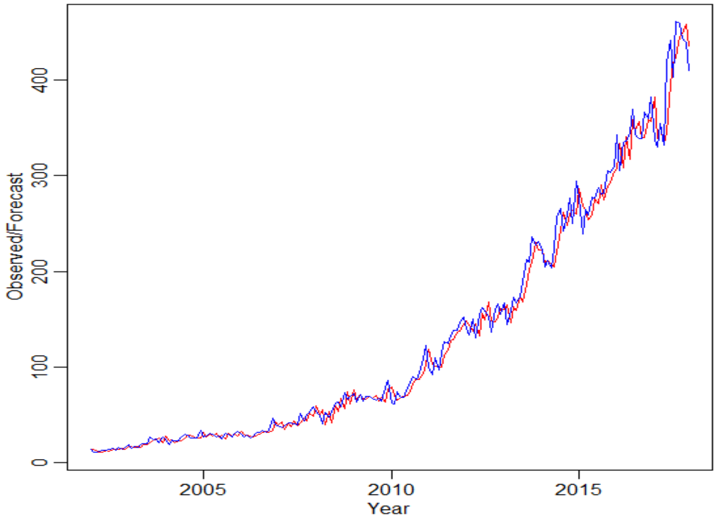


**Figure A8:** Plot of Residual Diagnostics for ARIMA(1, 1, 4) Model

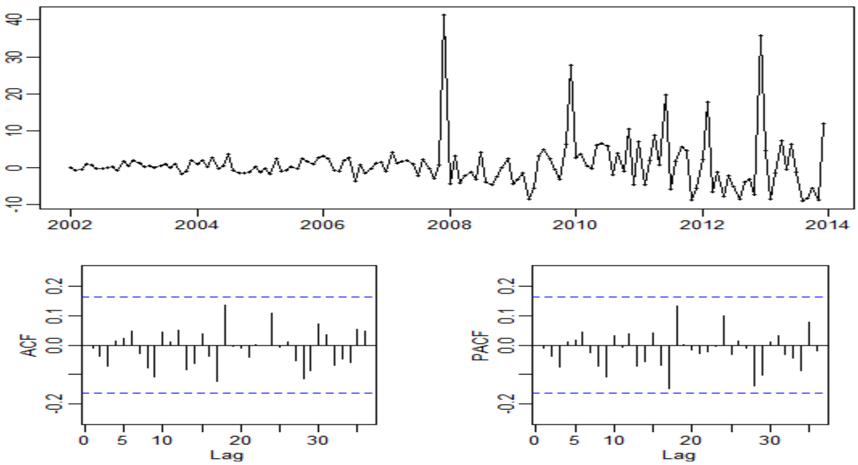

**Figure A8:** Plot of Residual Diagnostics for ARIMA(2, 1, 1) Model

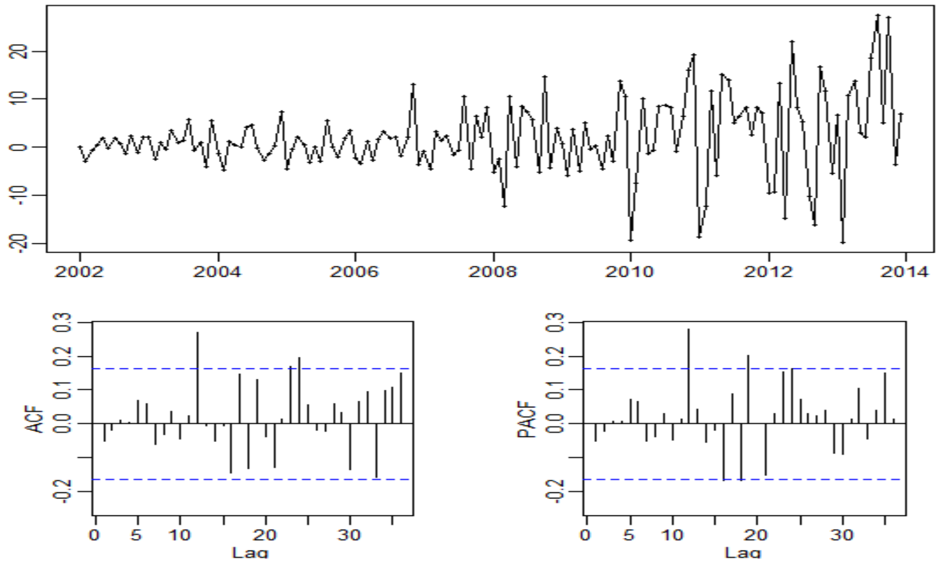


**Table A1.** Phillips-Perron Unit root test for VAT Revenue Data

| Variable | Level | | 1st Difference | |
|---|---|---|---|---|
| | *t-statistic* | *p-value* | *t-statistic* | *p-value* |
| *Total VAT* | 4.4414 | 1.0000 | -18.2144 | 0.0000 |
| *Domestic VAT* | 4.6342 | 1.0000 | -18.8238 | 0.0000 |
| *Import VAT* | 1.7617 | 0.9997 | -20.4580 | 0.0000 |

**Table A2.** ADF Unit root test pre-intervention series

| Variable | Level | | 1st Difference | |
|---|---|---|---|---|
| | *t-statistic* | *p-value* | *t-statistic* | *p-value* |
| *Total VAT* | 1.5847 | 1.0000 | -4.0085 | 0.0105 |
| *Domestic VAT* | 3.0153 | 1.0000 | -5.9712 | 0.0000 |
| *Import VAT* | 0.6122 | 0.9995 | -7.5460 | 0.0000 |

**Table A3.** Phillips-Perron Unit root test pre-intervention series

| Variable | Level | | 1st Difference | |
|---|---|---|---|---|
| | *t-statistic* | *p-value* | *t-statistic* | *p-value* |
| *Total VAT* | 4.7199 | 1.0000 | -16.5161 | 0.0000 |
| *Domestic VAT* | 0.4578 | 0.9847 | -26.3922 | 0.0000 |
| *Import VAT* | 4.8286 | 1.0000 | -16.4334 | 0.0000 |

**Table A4.** Ljung-Box Test for ARIMA(2, 1, 0) Residuals

| Lag | Test Statistic | p-value |
|---|---|---|
| 4 | 3.27 | 0.5139 |
| 8 | 8.65 | 0.3726 |
| 12 | 14.18 | 0.2892 |
| 16 | 15.60 | 0.4813 |
| 20 | 22.93 | 0.2925 |
| 24 | 38.30 | 0.0323 |

**Table A5.** ARCH-LM Test for ARIMA(2, 1, 0) Residuals

| Lag | Test Statistic | p-value |
|---|---|---|
| 4 | 15.0 | 0.0047 |
| 8 | 18.5 | 0.0178 |
| 12 | 25.9 | 0.0112 |
| 16 | 26.1 | 0.0533 |
| 20 | 31.9 | 0.0443 |
| 24 | 39.0 | 0.0272 |

**Table A6.** Ljung-Box Test for ARIMA(1, 1, 4) Residuals

| Lag | Test Statistic | p-value |
|---|---|---|
| 4 | 1.01 | 0.9080 |
| 8 | 2.38 | 0.9670 |
| 12 | 4.76 | 0.9650 |
| 16 | 6.81 | 0.9770 |
| 20 | 11.63 | 0.9280 |
| 24 | 13.59 | 0.9550 |

**Table A7.** ARCH-LM Test for ARIMA(1, 1, 4) Residuals

| Lag | Test Statistic | p-value |
|---|---|---|
| 4 | 0.112 | 0.9980 |
| 8 | 0.220 | 1.0000 |
| 12 | 0.631 | 1.0000 |
| 16 | 0.722 | 1.0000 |
| 20 | 3.021 | 1.0000 |
| 24 | 10.910 | 0.9900 |

**Table A8.** Ljung-Box Test for ARIMA(2, 1, 1) Residuals

| Lag | Test Statistic | p-value |
|---|---|---|
| 4 | 0.468 | 0.9765 |
| 8 | 2.341 | 0.9687 |
| 12 | 13.318 | 0.3463 |
| 16 | 16.748 | 0.4021 |
| 20 | 25.099 | 0.1977 |
| 24 | 37.069 | 0.0431 |

**Table A9.** ARCH-LM Test for ARIMA(2, 1, 1) Residuals

| Lag | Test Statistic | p-value |
|---|---|---|
| 4 | 39.1 | 0.0000 |
| 8 | 63.5 | 0.0000 |
| 12 | 91.6 | 0.0000 |
| 16 | 120.0 | 0.0000 |
| 20 | 140.0 | 0.0000 |
| 24 | 144.9 | 0.0000 |

**Table A10.** Forecast for ARIMA with Intervention for 2017

| Month | Total VAT | | Domestic VAT | | Import VAT | |
|---|---|---|---|---|---|---|
| | *Obser.* | *Predict.* | *Obser.* | *Predict.* | *Obser.* | *Predict.* |
| *January* | 632.80 | 665.27 | 294.68 | 285.21 | 338.13 | 382.52 |
| *February* | 590.59 | 636.44 | 260.62 | 288.86 | 329.97 | 338.99 |
| *March* | 620.93 | 607.39 | 266.51 | 279.31 | 354.42 | 350.42 |
| *April* | 627.52 | 620.83 | 295.48 | 283.57 | 332.04 | 334.21 |
| *May* | 693.76 | 620.82 | 274.58 | 285.68 | 419.17 | 344.46 |
| *June* | 724.05 | 678.86 | 283.01 | 274.48 | 441.04 | 396.56 |
| *July* | 690.42 | 705.64 | 287.01 | 284.32 | 403.41 | 417.40 |
| *August* | 755.72 | 693.31 | 294.41 | 284.04 | 461.30 | 423.69 |
| *September* | 777.37 | 745.84 | 317.60 | 290.67 | 459.77 | 445.74 |
| *October* | 757.95 | 761.17 | 314.15 | 304.18 | 443.80 | 448.50 |
| *November* | 732.81 | 758.92 | 293.20 | 308.52 | 439.61 | 458.16 |
| *December* | 749.94 | 742.08 | 340.06 | 309.82 | 409.89 | 435.15 |
| **TOTAL** | 8353.86 | 8236.57 | 3521.31 | 3478.66 | 4832.55 | 4775.80 |
| ***n*** | 12 | | 12 | | 12 | |
| ***MAD*** | 30.25 | | 14.8 | | 24.41 | |
| ***MSE*** | 1385.14 | | 289.78 | | 1036.99 | |
| ***RMSE*** | 37.22 | | 17.02 | | 32.2 | |
| ***MAPE*** | 4.37 | | 5.01 | | 5.97 | |

## APPENDIX-B

**Figure B1.** Plot of Observed and Fitted values of Holt Linear Trend Method

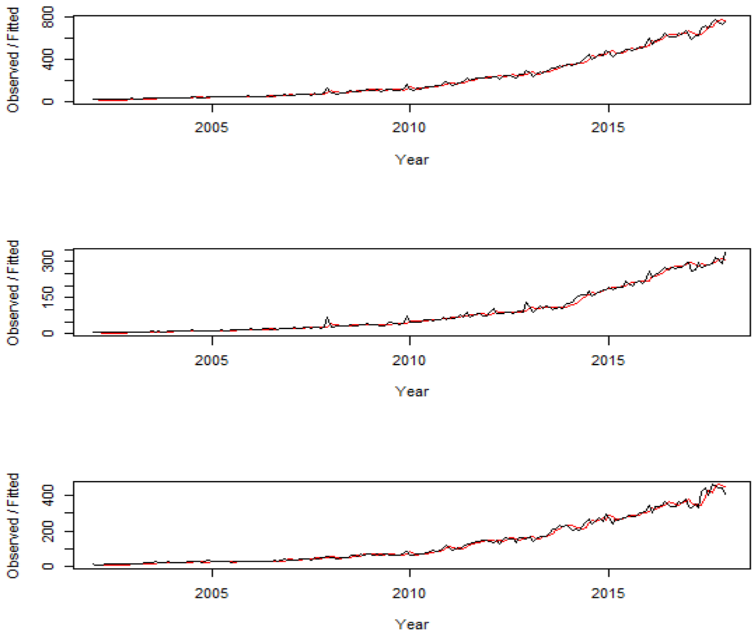


**Figure B2.** Residual Plot for Trend 1 (Total VAT)

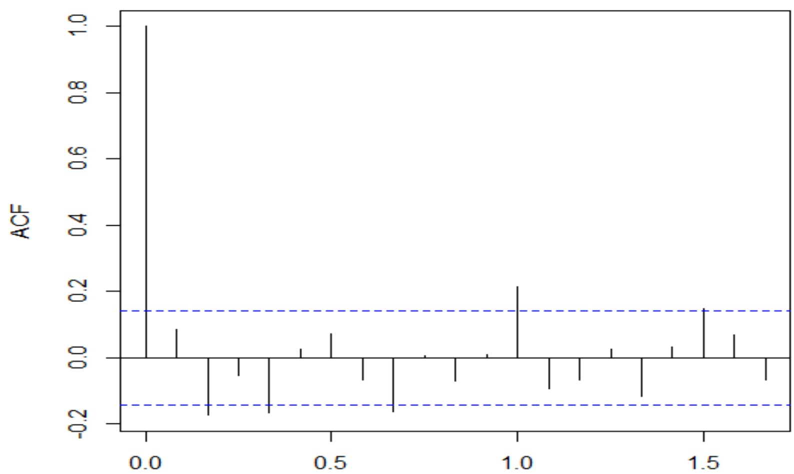

**Figure B3.** Residual Plot for Trend 2 (Domestic VAT)

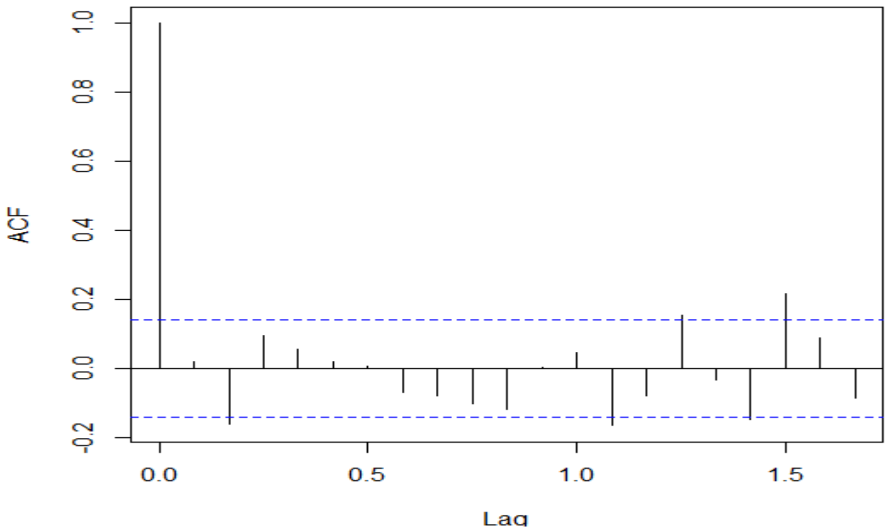


**Figure B4.** Residual Plot for Trend 3 (Import VAT)

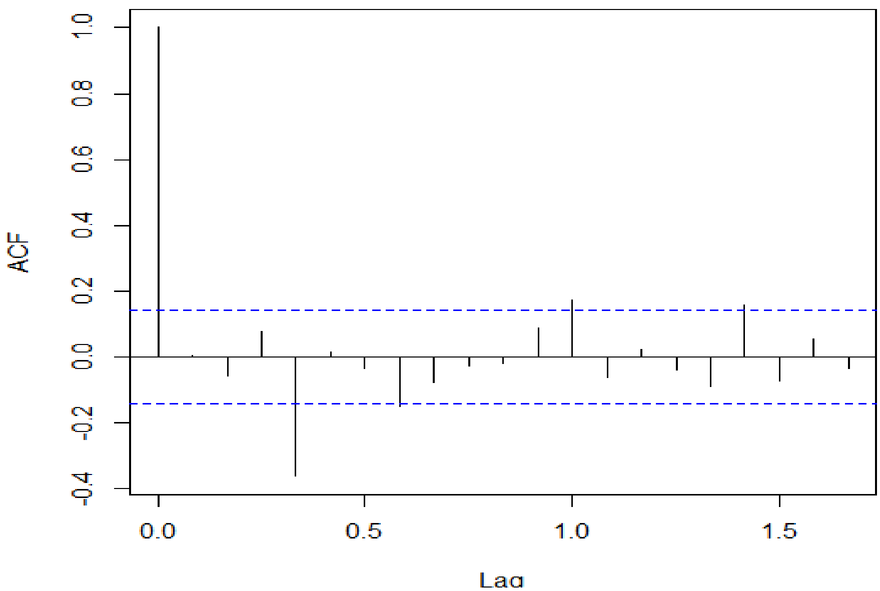

**Table B1.** Observed and Predicted Monthly VAT revenue from Holt Linear Trend model for 2017

| Month | Total VAT | | Domestic VAT | | Import VAT | |
|---|---|---|---|---|---|---|
| | *Obser.* | *Predict.* | *Obser.* | *Predict.* | *Obser.* | *Predict.* |
| *January* | 632.80 | 669.41 | 294.68 | 292.7 | 338.13 | 378.45 |
| *February* | 590.59 | 678.71 | 260.62 | 297.15 | 329.97 | 383.00 |
| *March* | 620.93 | 688.01 | 266.51 | 301.59 | 354.42 | 387.55 |
| *April* | 627.52 | 697.31 | 295.48 | 306.04 | 332.04 | 392.10 |
| *May* | 693.76 | 706.61 | 274.58 | 310.49 | 419.17 | 396.65 |
| *June* | 724.05 | 715.91 | 283.01 | 314.93 | 441.04 | 401.20 |
| *July* | 690.42 | 725.21 | 287.01 | 319.38 | 403.41 | 405.74 |
| *August* | 755.72 | 734.50 | 294.41 | 323.83 | 461.30 | 410.29 |
| *September* | 777.37 | 743.80 | 317.60 | 328.28 | 459.77 | 414.84 |
| *October* | 757.95 | 753.10 | 314.15 | 332.72 | 443.80 | 419.39 |
| *November* | 732.81 | 762.40 | 293.20 | 337.17 | 439.61 | 423.94 |
| *December* | 749.94 | 771.70 | 340.06 | 341.62 | 409.89 | 428.48 |
| **TOTAL** | 8353.86 | 8646.67 | 3521.31 | 3805.9 | 4832.55 | 4841.63 |
| ***n*** | 12 | | 12 | | 12 | |
| ***MAD*** | 35.70 | | 24.05 | | 33.82 | |
| ***MSE*** | 1905.63 | | 774.77 | | 1420.96 | |
| ***RMSE*** | 43.65 | | 27.83 | | 37.70 | |
| ***MAPE*** | 5.45 | | 8.48 | | 8.74 | |

## APPENDIX-C

**Table C1.** Measuring Accuracy of the Prediction Between Gra Target And ARIMA with Intervention Forecast

| TIME | Total VAT | | | Domestic VAT | | | Import VAT | | |
|---|---|---|---|---|---|---|---|---|---|
| | ACTUAL | TARGET | FORECAST | ACTUAL | TARGET | FORECAST | ACTUAL | TARGET | FORECAST |
| *Jan-17* | 632.8 | 651.25 | 667.73 | 294.68 | 289.42 | 285.21 | 338.13 | 361.83 | 382.52 |
| *Feb-17* | 590.59 | 570.7 | 627.85 | 260.62 | 257.07 | 288.86 | 329.97 | 313.63 | 338.99 |
| *Mar-17* | 620.93 | 664.57 | 629.73 | 266.51 | 281.2 | 279.31 | 354.42 | 383.37 | 350.42 |
| *Apr-17* | 627.52 | 707.67 | 617.78 | 295.48 | 322.17 | 283.57 | 332.04 | 385.5 | 334.21 |
| *May-17* | 693.76 | 726.79 | 630.14 | 274.58 | 323.37 | 285.68 | 419.17 | 403.42 | 344.46 |
| *Jun-17* | 724.05 | 770.51 | 671.04 | 283.01 | 324.07 | 274.48 | 441.04 | 446.44 | 396.56 |
| *Jul-17* | 690.42 | 773.83 | 701.72 | 287.01 | 325.77 | 284.32 | 403.41 | 448.06 | 417.4 |
| *Aug-17* | 755.72 | 770.1 | 707.73 | 294.41 | 329.48 | 284.04 | 461.3 | 440.62 | 423.69 |
| *Sep-17* | 777.37 | 744.7 | 736.41 | 317.6 | 310.2 | 290.67 | 459.77 | 434.5 | 445.74 |
| *Oct-17* | 757.95 | 773.35 | 752.68 | 314.15 | 320 | 304.18 | 443.8 | 453.35 | 448.5 |
| *Nov-17* | 732.81 | 798.43 | 766.68 | 293.2 | 325.4 | 308.52 | 439.61 | 473.03 | 458.16 |
| *Dec-17* | 749.94 | 894.58 | 744.97 | 340.06 | 390.48 | 309.82 | 409.89 | 504.1 | 435.15 |
| *Jan-18* | 696.36 | 709.64 | 687.77 | 298.62 | 271.74 | 343.88 | 397.74 | 437.9 | 343.88 |
| *Feb-18* | 674.32 | 714.11 | 651.41 | 314.92 | 330.41 | 325.71 | 359.4 | 383.7 | 325.71 |
| *Mar-18* | 714.6 | 773.08 | 663.93 | 308.57 | 353.16 | 331.97 | 406.03 | 419.92 | 331.97 |
| *Apr-18* | 690.16 | 817.06 | 691.16 | 322.82 | 372.44 | 345.58 | 367.34 | 444.62 | 345.58 |
| *May-18* | 699.64 | 855.65 | 696.52 | 299.2 | 375.34 | 348.26 | 400.44 | 480.31 | 348.26 |
| *Jun-18* | 752.25 | 925.39 | 702.3 | 342.08 | 383.11 | 351.15 | 410.17 | 542.28 | 351.15 |
| *Jul-18* | 802.02 | 924.47 | 701.3 | 391.68 | 401.38 | 350.65 | 410.34 | 523.09 | 350.65 |
| *Aug-18* | 826.75 | 955.39 | 719.05 | 416.58 | 396.08 | 359.53 | 410.17 | 559.32 | 359.53 |
| *Sep-18* | 722.15 | 772.82 | 725.86 | 369.92 | 342.71 | 362.93 | 352.23 | 430.11 | 362.93 |
| *Oct-18* | 784.63 | 805.99 | 731.42 | 394.65 | 349.75 | 365.71 | 389.98 | 456.24 | 365.71 |
| *Nov-18* | 775.73 | 844.68 | 730.64 | 385.61 | 349.46 | 365.32 | 390.12 | 495.22 | 365.32 |
| *Dec-18* | 833.81 | 945.47 | 759.61 | 425.38 | 438.7 | 379.8 | 408.43 | 506.77 | 379.8 |
| *Jan-19* | 725.02 | 787.53 | 758.46 | 380.16 | 388.43 | 379.23 | 344.86 | 399.1 | 379.23 |
| *Feb-19* | 681.25 | 709.82 | 743.98 | 354.12 | 345.02 | 371.99 | 327.13 | 364.8 | 371.99 |
| *Mar-19* | 758.75 | 774.08 | 754.55 | 403.8 | 377.39 | 377.27 | 354.95 | 396.68 | 377.27 |
| *Apr-19* | 696.51 | 780.7 | 778.27 | 381.55 | 421.45 | 389.13 | 314.96 | 359.25 | 389.13 |
| *May-19* | 726.22 | 817.88 | 770.09 | 415.04 | 434.93 | 385.04 | 311.18 | 382.95 | 385.04 |
| *Jun-19* | 688.27 | 826.18 | 775.25 | 435.42 | 434.93 | 387.62 | 252.85 | 391.25 | 387.62 |
| *Jul-19* | 729.55 | 829.39 | 787.41 | 435.41 | 437.23 | 393.71 | 294.14 | 392.17 | 393.71 |
| *Aug-19* | 710.06 | 842.27 | 797.33 | 418.72 | 451.47 | 398.67 | 291.34 | 390.8 | 398.67 |
| *Sep-19* | 720.79 | 848.26 | 816.13 | 439.67 | 446.83 | 408.07 | 281.12 | 401.43 | 408.07 |
| *Oct-19* | 717.8 | 896.57 | 819.75 | 423.49 | 469.7 | 409.87 | 294.31 | 426.87 | 409.87 |
| *Nov-19* | 812.93 | 895.76 | 814.82 | 513.65 | 470.7 | 407.41 | 299.28 | 425.06 | 407.41 |
| *Dec-19* | 963.04 | 907.68 | 846.36 | 636 | 498.73 | 423.18 | 327.04 | 408.95 | 423.18 |
| | | | | | | | | | |
| | | GRA TARGET | ARIMA | | GRA TARGET | ARIMA | | GRA TARGET | ARIMA |
| ***n*** | | 36 | 36 | | 36 | 36 | | 36 | 36 |
| ***MAD*** | | 76.83 | 45.74 | | 30.21 | 30.4 | | 66.52 | 50.67 |
| ***MSE*** | | 8,290.23 | 3,279.35 | | 1,551.97 | 9,605.37 | | 6,186.77 | 7,207.53 |
| ***RMSE*** | | 91.05 | 57.27 | | 39.4 | 98.01 | | 78.66 | 84.9 |
| ***MAPE*** | | 10.6 | 6.16 | | 8.95 | 7.58 | | 19.83 | 15.19 |