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INVESTIGATION OF VAR WITH GARCH FAMILY MODELS: ONTAXES REVENUE VOLATILITY MODELING

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Abstract

Accurate future values forecast is the tools Policy makers for tax revenue planning. It's owed the fact that tax revenue volatility is a valuable measure of uncertainty about the economic environment of a country. This paper applies multivariate time series analysis to the monthly (₦ Naira) tax revenue data spanning from January 1981 to December 2018 to examine the behavior of tax revenue in Nigeria. To capture the volatility effect in tax revenue data, the paper applies vector autoregression (VAR) and GARCH family models. The study divulges that tax revenue series displays the empirical consistencies such as non-normality non-stationarity, clustering volatility, and serial correlation that validate the application of the GARCH family methods. The study indicates that tax revenue behavior is usually induced by past data about tax revenue. It's also inferring that previous monthly's volatility in tax revenue can distress present volatility of tax revenue. In addition, the estimate for asymmetric volatility

KEYWORDS: *Data, GARCH, Modelling, Tax revenue, Volatility*

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suggests that positive shocks imply a higher next period conditional variance than negative shocks of the same sign. The main policy implication of these results is that since tax revenue volatility may increase administrative costs and reduce the gains to income revenue, knowledge of tax revenue volatility estimation and forecasting is significant for fiscal policy and tax revenue administrative management.

INTRODUCTION

Breeding an analytic time series model to describe the relationships among highly correlated explanatory variables has been quite challenging due to the difficult nature and the inadequate knowledge of the basic mechanisms that are accountable for the relationship. In some cases, the univariate time series analysis is adequate. While, in some situations, it may be restricted. VAR modeling is regarded as appropriate for the estimation if it does not exhibit significant autocorrelation and heteroscedastic effects which can be captured by the nonlinear multivariate GARCH family models. The multivariate GARCH method is the most suitable model for various interconnected time series with a suitable multi-dimensional model. In particular, the volatility process needs some information from the positive semi-definite matrices and multivariate GARCH can correspond to covariate matrices at each point in time (Boussama et al., 2011). El Hedi Arouri et al. (2015) utilized the VAR-GARCH framework to explore volatility spill-overs amongst stock market and gold prices from 2004 to 2011.

The research compared several multivariate volatility models that were frequently adopted in finance literature like BEKK GARCH. The results proved the superiority of VAR-GARCH over other multivariate GARCH model specifications. Silva et al., (2020) utilize a bivariate VAR-GARCH model developed an index of positive and negative news to measure the impact of press releases. Their results reveal an average spread impact of the news for variables used as proxies for Brazilian asset prices. Ayele et al., (2017) investigated main macroeconomic variables that influence the variable's volatility (gold prices) and formulate various ARCH family models to assess the volatility of gold prices in the Ethiopian market. Besides, the interest of their study is to find out whether GARCH family models are an improvement over the EWMA-type models in terms of modelling and forecasting price volatility of gold

MacDonald et al. (2018) investigated co-movements of volatility and effects of spill-over among the Economies of the Eurozone. Likewise, the GARCH-BEKK

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technique might evaluate the volatility linkage, the returns, and spill-over volatility effects (Kumar, 2013). Ashwin et al., (2010) studied the co-movement amongst some selected world stock markets for both developed and emerging economy utilizing VAR-fGARCH model. The result indicates average daily positive returns for some selected period and high volatility of stock market during the period for develop stock market and low for emerging markets. The result also reveals that the correlation amongst the stock markets were low for emerging markets. Meaning that the stock markets have attractive portfolio diversification opportunities for emerging markets investors. The original formulation of the GO-GARCH model involved the stronger assumption of independence of the components of y_t, but for the methods presented in the present paper, the conditional uncorrelatedness assumption (Fan et al. (2008)

The VAR-GARCH Model

The VAR-GARCH model incorporates a standard GARCH (1,1) process (Chung et al., 2012,) for the orthogonalized error of each VAR equation:11

$$y_t = B_0 + \sum_{i=1}^{p} B_i y_{t-i} + v_t$$

$$v_t = A^{-1} H_t^{0.5} \varepsilon_t, \varepsilon_t \sim N(0, I_k), \;\; H_t \equiv diag(h_{1,t}, ..., h_{k,t}) \quad (3.68)$$

$$h_{i,t} = a_{0,i} + a_{1,i} v_{i,t-1}^2 + a_{2,i} h_{i,t-1}, \; a_{0,i} > 0, a_{1,i} + a_{2,i} < 1, \; i = 1, k$$

where *A = a D* is a lower triangular matrix with ones on the diagonal and non-zero coefficients below the diagonal. In this GARCH formulation, each variable is treated independently, with the conditional variance $h_{i,t}$ a function of one lag of itself and one lag of the squared error from the VAR equation. We impose conditions to ensure the positivity and stationarity of each volatility process.

The VAR-EWMA Model

EWMA is a technique that presumes value changes over time. Utilizing EWMA for volatility modelling, the expression is written as:

$$\sigma = \sqrt{(1-\lambda)\sum_{t=n}^{t=i} \lambda^t (X_t - \mu)^2} \qquad (3.69)$$

Where *n* is the number of months and λ is an exponential factor. In expression, μ is the μ value of the distribution, which is usually assumed to be zero. The expression of volatility for exponential weighted is expressed as:

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$$\sigma_{i,j} = \sqrt{(1-\lambda)\sum_{j=0}^{\infty} \lambda^j r_{i-j}^2} \qquad (3.70)$$

This expression is directly measured up with the GARCH technique. The vital aspect of the ability of the technique is the selected value factor. For EWMA estimate, the required number of days/months can be estimated as follows (Best, 1999)

In equation λ is an exponential factor, $r_{i,j}$, denote return of asset logarithmic *i* at time t. Hence, $r_{i,j}$, is estimated by the $\ln\left(P_{i,t} / P_{i,t-1}\right)$ formula.

The VAR-GO-GARCH Model

Considering the *k*-variate VAR technique of order one *I*(1) for the mean equation with the representation as:

$$y_t = \mu + By_{t-1} + \varepsilon_t \qquad (3.71)$$

where VAR$\left(\varepsilon_t \mid y_{t-1}, \ldots y_1\right) = H_t, y_t$ is a $k\times1$ vector of returns, μ is a $k\times1$ vector of coefficients, the autoregressive coefficients *B* is a $k\times k$ matrix, and ε_t is a $k\times1$ vector of innovations

The VAR-fGARCH Model

The conditional variance of the fGARCH technique in (3.62) at time *h*+1 is given by

$$\sigma_{h+12}^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{h+1-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{h+1-j}^2 \qquad (3.78)$$

where at time h all the past values a_{h+1-i}^2 and σ_{h+1-j}^2 are known for all $i \le m$ and $j \le s$. Therefore, from forecast origin *h* $\sigma_h^2(1)$ equals σ_{h+1}^2 for the 1-step ahead forecast given as:

$$\sigma_h^2(1) = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{h+1-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{h+1-j}^2 \qquad (3.79)$$

In particular, for a GARCH(1,1) process with $\alpha_0 = 0$, the 1-step-ahead forecast from forecast origin *h* is

$$\sigma_h^2(1) = \alpha_1 a_h^2 + \beta_1 \sigma_h^2$$

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VAR-GARCH Model

Figure. 5.1 and 5.2 gives the time plots of the time-varying correlations between the tax components returns. The red line denotes the estimated values spiking on the actual values indicating the performance of the combination of the VAR-GARCH model is done well, by removing the autocorrelation, but the underlying assumption for the VAR-GARCH model is that volatility changes over time. When σ_i^2 is high, there is the tendency σ_{i+1}^2 to be high and vice-versa.

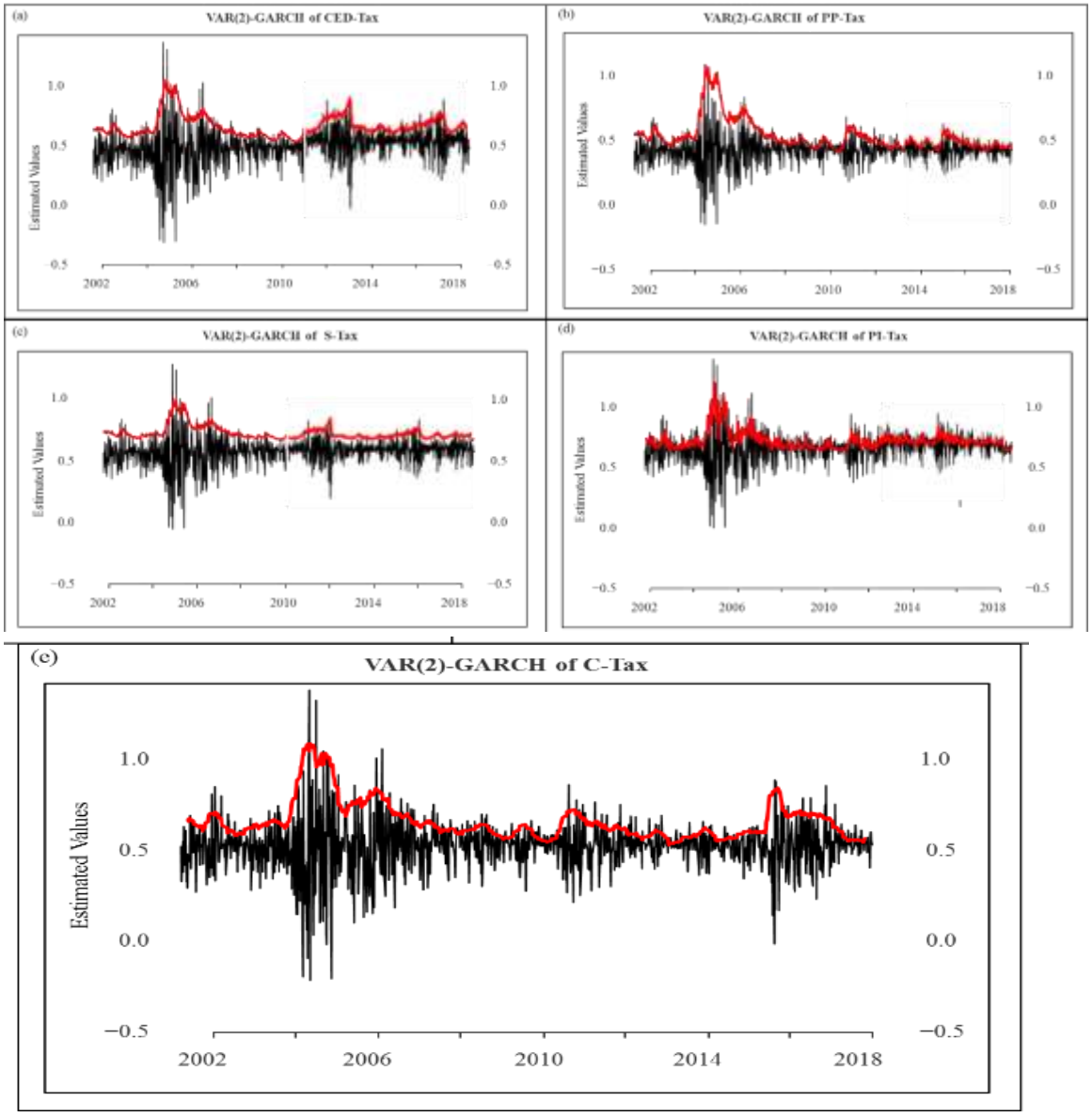

Figure. 5.1 (a)-(e) Indicating estimated values of the VAR(2)-GARCH model

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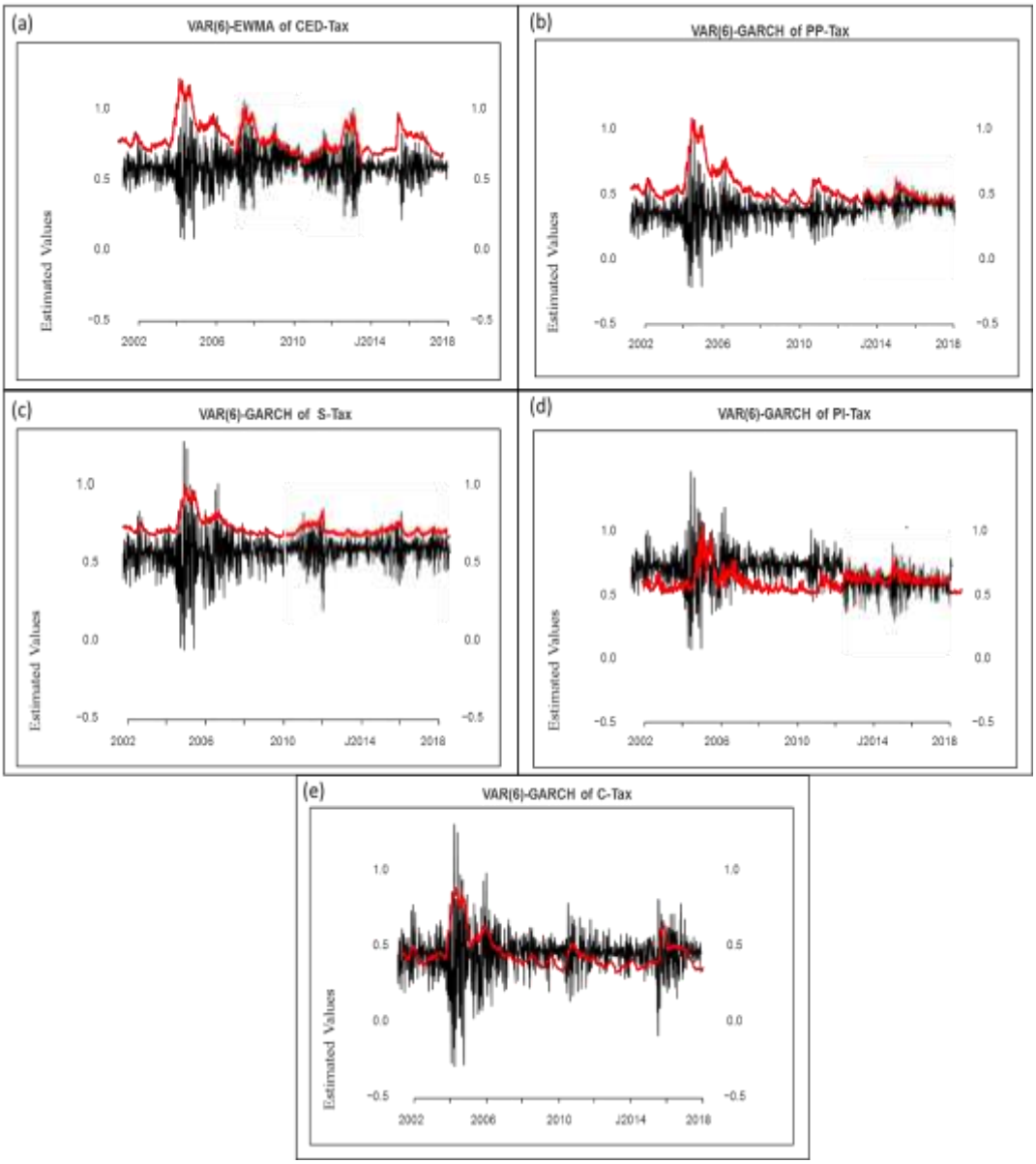

Figure. 5.2 (a)-(e) Indicating estimated values of the VAR(6)-GARCH model

The result from Table 5.1 showed that the estimates of α and β are statistically significant with the probability of less than 5% significance level. The conditional variance was finite and the series was firmly stationary. Though, the sum of parameters α and β for the VAR-GARCH model is shown to approach one. This value indicated that a large long-term influence shock on the conditional correlation is present in the volatility series (Morema & Bonga-Bonga., 2020; Park et al., 2017).

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Table 5.1. VAR-GARCH parameter estimation.

		Estimates	Standard error	Probability
VAR(2)				
Parameter	α	0.0461	0.0124	0.0000
	β	0.9681	0.9792	0.0015
Information Criteria	AIC	29.1497		
	BIC	29.5131		
Log-likelihood		-2874.4111		
VAR(6)				
Parameter	α	0.0572	0.0171	0.0023
	β	0.9591	0.9612	0.0125
Information Criteria	AIC	29.4527		
	BIC	29.7324		
Log-likelihood		-2224.4551		

Table 5.2 shows the estimated performance of the models in terms of error measurements, that is mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) we considered the model with minimum values, such that we can select a model that yields more accurate results.

Table 5.2 The Accuracy Measures VAR-GARCH Model

Model	MAE	MAPE	RMSE
In-sample			
VAR(2)-Garch	0.5432	22.8923	22.8977
VAR(6)-GARCH	0.5954	22.9856	22.9888
Out-sample			
VAR(2)-GARCH	0.2732	23.4365	23.4367
VAR(6)-GARCH	0.2991	23.8768	23.8798

VAR-EWMA Model

Figure. 5.3 and 5.4 gives the time plots of the time-varying correlations between the tax components returns. The red line denotes the estimated values spiking on the actual values indicating the performance of the combination of VAR-EWMA model has performed better, by eliminating the autocorrelation, but the

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underlying assumption for the VAR-EWMA model is that, volatility changes over time. When U_i^2 is high, there is the tendency U_{i+1}^2 to be high and vice-versa

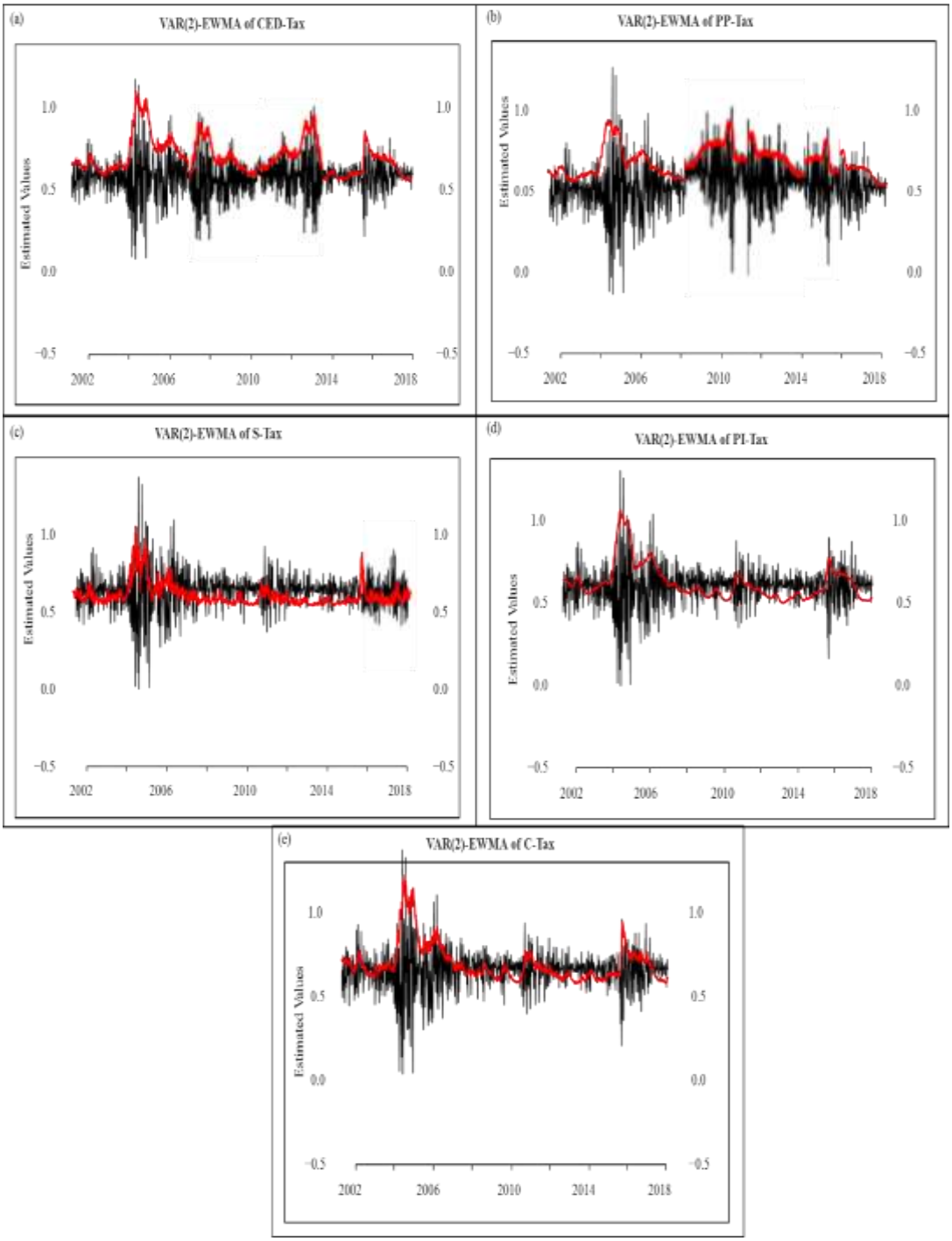

Figure. 5.3 (a)-(e) indicating estimated values of the VAR(2)-EWMA model

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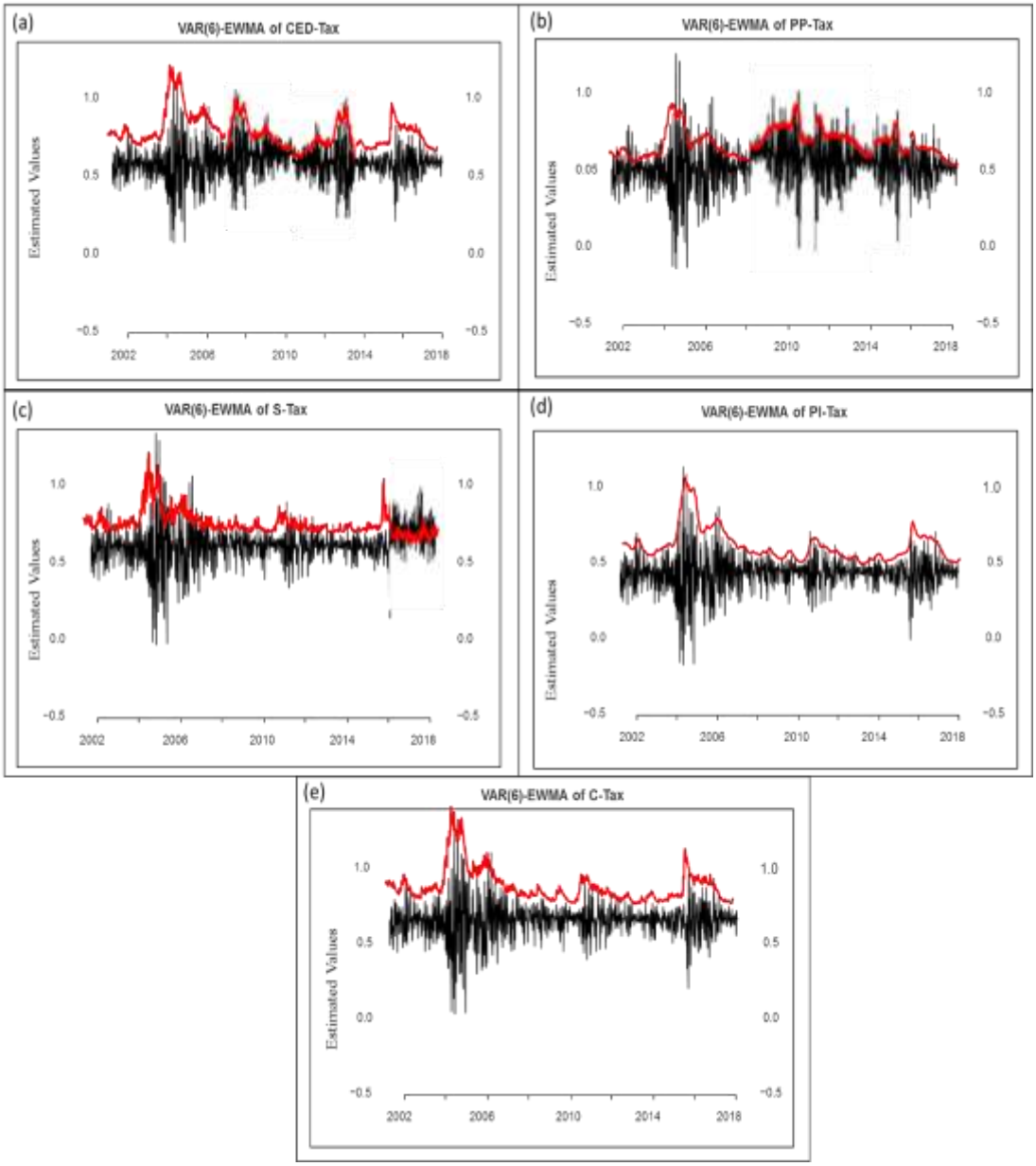

Figure. 5.4 (a)-(e) indicating estimated values of the VAR(6)-EWMA model

The result from Table 5.3 showed that the estimates of α and β are statistically significant with the probability of less than 5% significance level. The conditional variance was finite and the series were strictly stationary. But, the sum of parameters α and β for the VAR-EWMA model is divulged to approach one. This value displayed that a bulky long-term influential shock on the conditional correlation is shown in the volatility series (Halkos & Tsirivis 2019; Zivkov et al., 2020).

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Table 5.3 VAR-EWMA parameter estimation.

		Estimates	Standard error	Probability
VAR(2)-EWMA				
Parameter	α	0.0511	0.0154	0.0000
	β	0.9712	0.9622	0.0021
Information Criteria	AIC	31.1007		
	BIC	31.1018		
Log-likelihood		-2834.4721		
VAR(6)-EWMA				
Parameter	α	0.5221	0.0432	0.0121
	β	0.9621	0.9561	0.0127
Information Criteria	AIC	31.7851		
	BIC	31.7892		
Log-likelihood		-2464.7621		

Table 5.4 shows the estimated performance of the models in terms of error measurements, that is mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) we considered the model with minimum values, such that we can select a model that yields more accurate results.

Table 5.4 The Accuracy Measures VAR-EWMA Model

Model	MAE	MAPE	RMSE
In-sample			
VAR(2)-EWMA	0.5619	22.2717	28.2928
VAR(6)-EWMA	0.5792	22.3034	22.3075
Out-sample			
VAR(2)-EWMA	0.2422	22.8672	22.8691
VAR(6)-EWMA	0.2244	22.6741	22.6777

VAR-GO-GARCH Model

Figure. 5.5 and 5.6 gives the time plots of the time-varying correlations between the tax components returns. The red line denotes the estimated values spiking on the actual values indicating the performance of the combination of VAR-GO-GARCH model has performed better, by eradicating the autocorrelation, but the

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underlying assumption for the VAR-GO-GARCH model is that, volatility changes over time. When σ_i^2 is high, there is the tendency σ_{i+1}^2 to be high and vice-versa

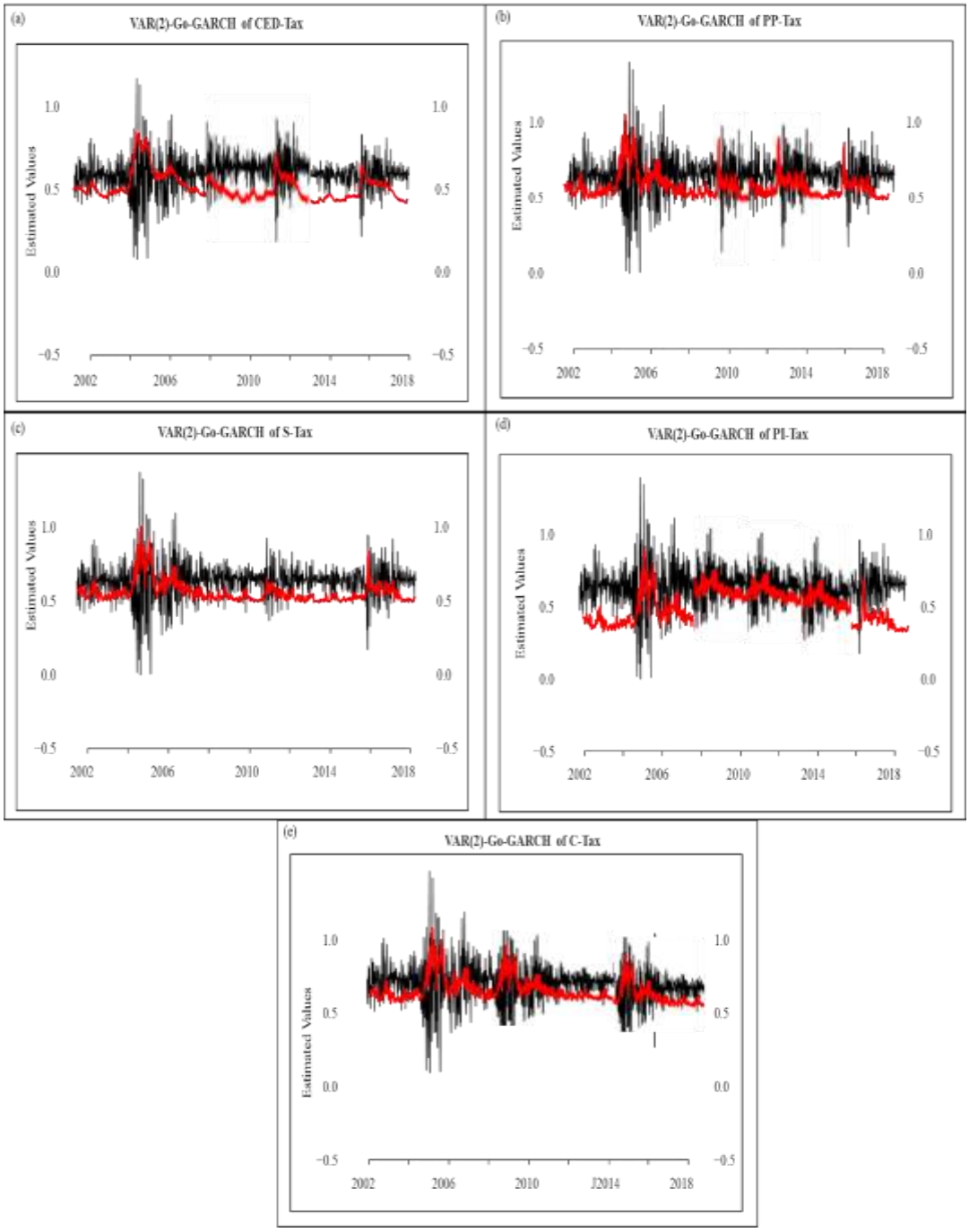

Figure. 5.5 (a)-(e) indicating estimated values of the VAR(2)-GO-GARCH model

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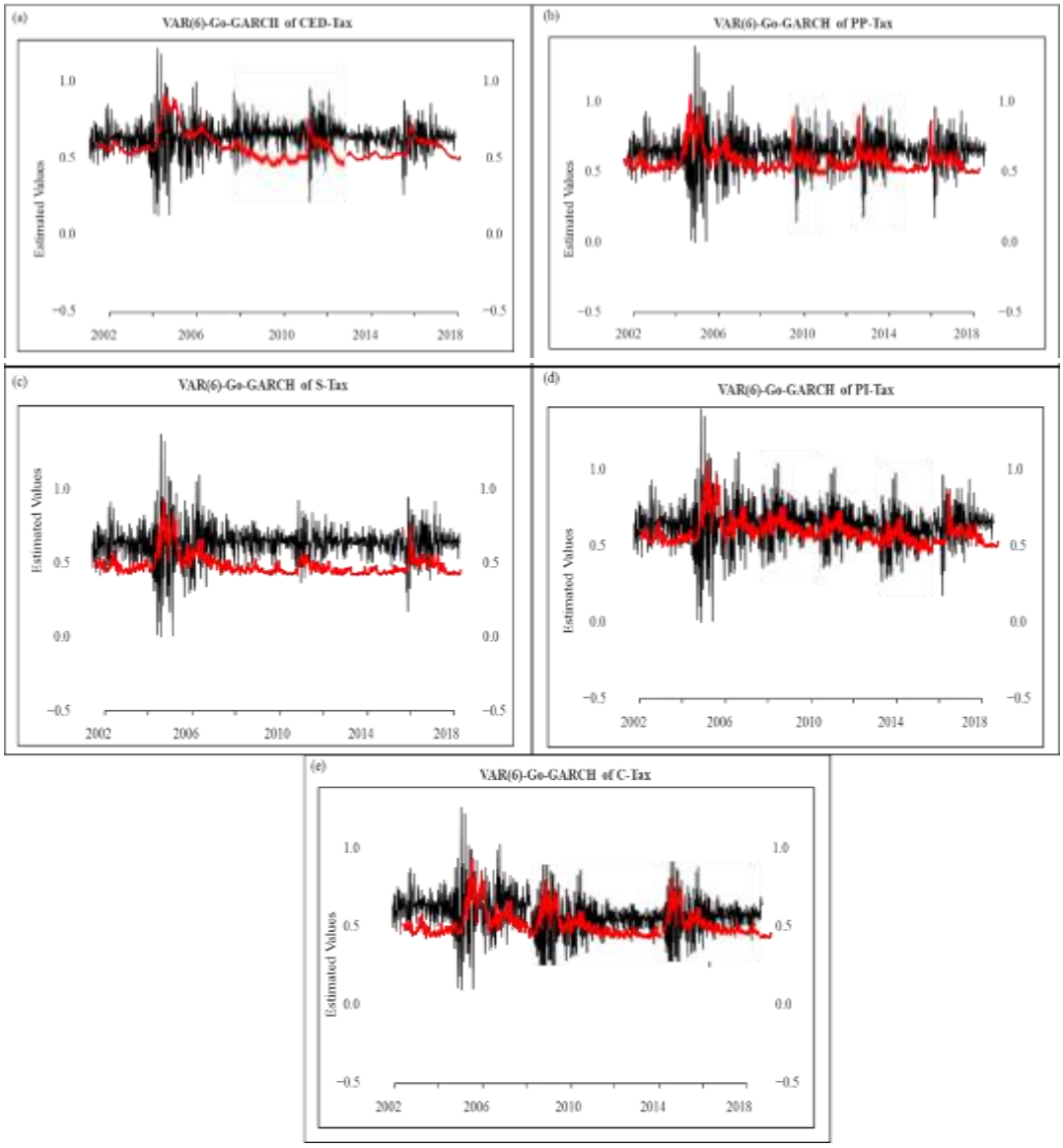

Figure. 5.6 (a)-(e) indicating estimated values of the VAR(6)-GO-GARCH model

The result from Table 5.5 exhibited that the estimates of α and β are statistically significant with the probability of less than 5% significance level. The conditional variance was restricted and the series were stringently stationary. Nevertheless, the sum of parameters α and β for the VAR-Go-GARCH model is appeared to approach one. This value indicated that a bulky long-term influence shock on the conditional correlation is portrayed in the volatility series (Sadorsky 2014; Park et al., 2017).

Table 5.5 VAR-Go-GARCH parameter estimation.

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		Estimates	Standard error	Probability
VAR(2)				
Parameter	α	0.0411	0.0114	0.0000
	β	0.9543	0.9122	0.0019
Information Criteria	AIC	29.8327		
	BIC	29.8338		
Log-likelihood		-2894.4121		
VAR(6)				
Parameter	α	0.07711	0.03311	0.0231
	β	0.9543	0.9122	0.0121
Information Criteria	AIC	29.9877		
	BIC	29.9898		
Log-likelihood		-2774.3231		

Table 5.6 exhibits the evaluated performance of the models in terms of error measurements, that is mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) we measured the model with minimum values, such that we can select a model that accedes more precise results.

Table 5.6 The accuracy measures for the VAR-GO-GARCH model

Model	MAE	MAPE	RMSE
In-sample			
VAR(2)-GO-GARCH	0.4029	21.8973	21.8994
VAR(6)-GO-GARCH	0.4551	21.9932	21.9984
Out-sample			
VAR(2)-GO-GARCH	0.1954	20.9867	20.9898
VAR(6)-GO-GARCH	0.2131	20.9957	20.9991

VAR-fGARCH model

The fGARCH model was used to model the residuals of the fitted VAR(2) model and the result of the parameter estimation is displayed in Table 5.10. For this VAR(2)-fGARCH model, parameter a measured the impact of past shocks on conditional correlations while parameter *p* measured the impact of past correlations. The dynamic part was captured by coefficient *a* which accounted for the impact of shocks on current conditional correlations (Adammer et al., 2016; Norrulashikin et al., 2018).

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Graphical presentation of VAR-fGARCH Performance

Figure. 5.7 and 5.8 gives the time plots of the time-varying correlations between the tax components returns. The red line represents the estimated values with less spiking on the actual values signifying better performance of the combination of the VAR-fGARCH model, by eliminating the autocorrelation, but the underlying assumption for the VAR-fGARCH model is that volatility changes over time.

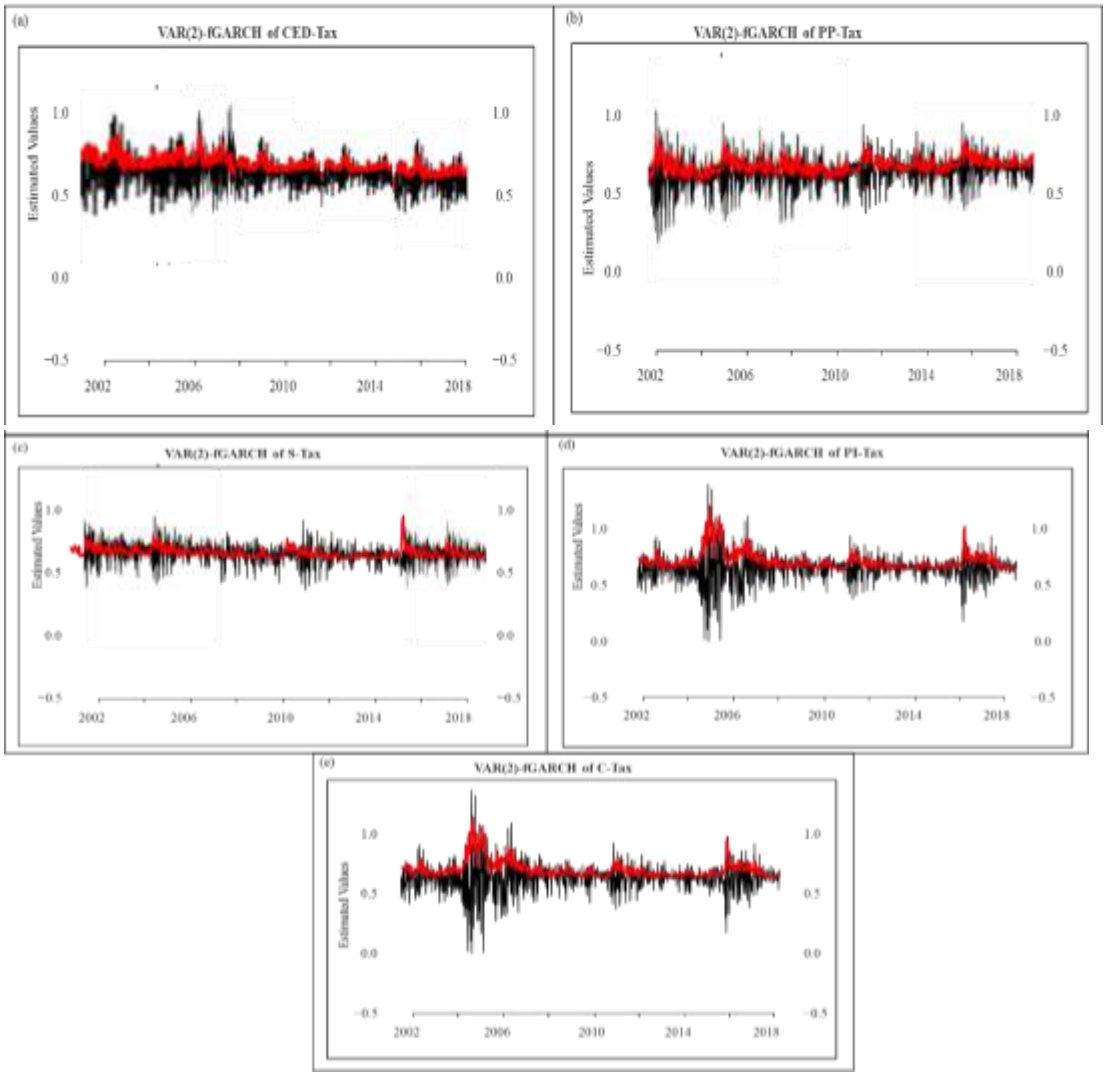

Figure. 5.7 (a)-(e) Indicating estimated values of the parameter for the VAR(2)-fGARCH model

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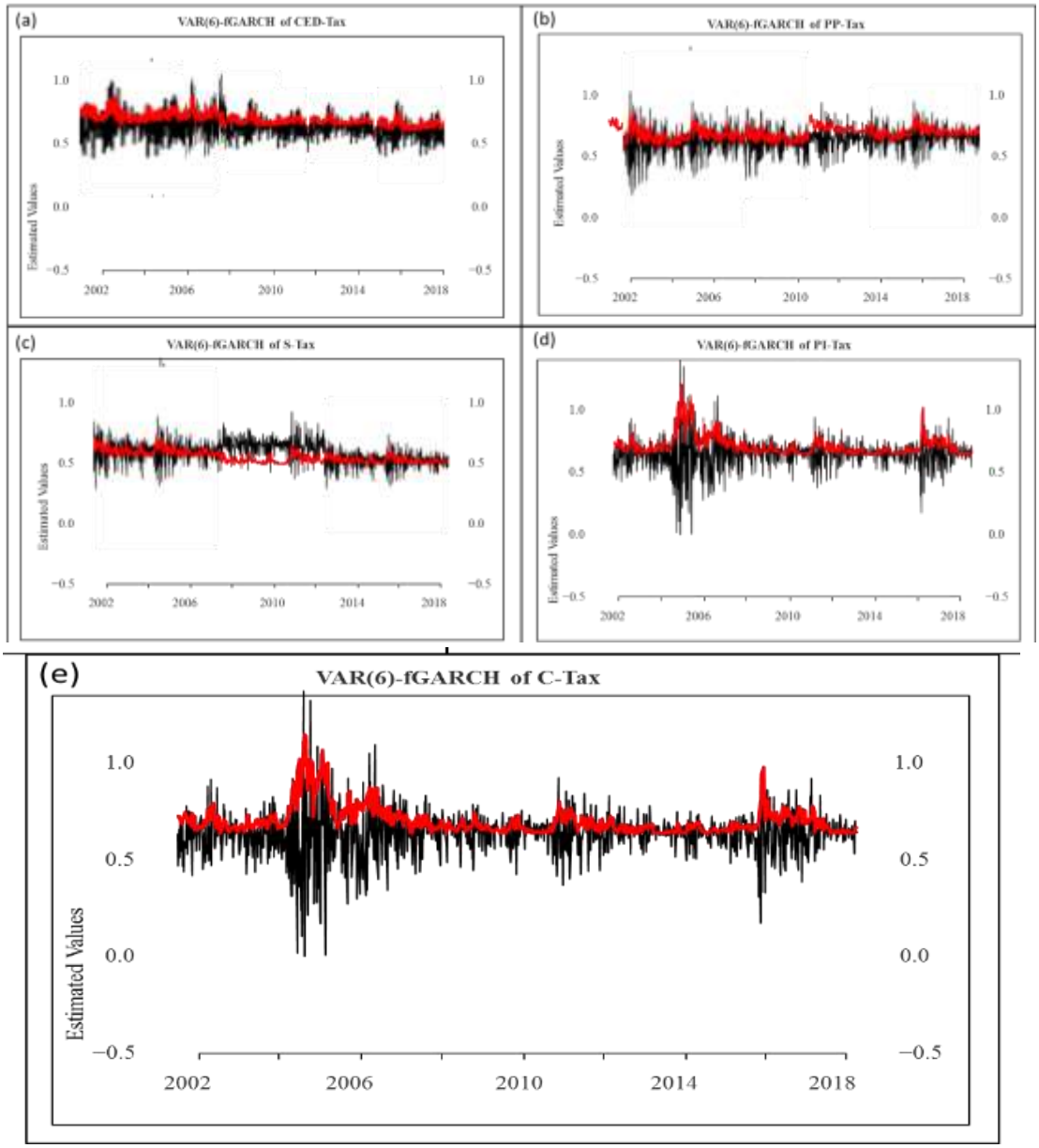

Figure. 5.8 (a)-(e) Indicating estimated values of the parameter for the VAR(6)-fGARCH model

VAR-fGARCH Model Estimation

The result from Table 5.7 showed that the estimates of α and β are statistically significant with the probability of less than 5% significance level. The conditional variance was finite and the series were strictly stationary. However, the sum of parameters α and β for the VAR-fGARCH model is shown to approach one. This

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value indicated that a large long-term influence shock on the conditional correlation is present in the volatility series (Sadorsky 2014; Park et al., 2017).

Table 5.7 VAR-fGARCH parameter estimation.

		Estimates	Standard error	Probability
VAR(2)-fGARCH				
Parameter	α	0.0391	0.0094	0.0000
	β	0.9451	0.8992	0.0007
Information Criteria	AIC	28.1157		
	BIC	28.4531		
Log-likelihood		-2974.4221		
VAR(6)-fGARCH				
Parameter	α	0.0411	0.0143	0.0067
	β	0.9393	0.8881	0.0121
Information Criteria	AIC	28.4347		
	BIC	28.4392		
Log-likelihood		-2522.2111		

Table 5.8 shows the estimated performance of the models in terms of error measurements, that is mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) we considered the model with minimum values, such that we can select a model that yields more accurate results.

Table 5.8 The accuracy measures for the VAR-fGARCH model

Model	MAE	MAPE	RMSE
In-sample			
VAR(2)-fGARCH	0.3944	15.828	20.3997
VAR(6)-fGARCH	0.4345	15.899	20.5455
Out-sample			
VAR(2)-fGARCH	0.1251	11.8767	13.8901
VAR(6)-fGARCH	0.1653	11.9934	13.9789

In other to draw a meaningful conclusion on the model, it is essential to examine whether or not the residuals passed the autocorrelation test, and to measure the adequacy of the model (see Table 5.9). The autocorrelation test of the residuals

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from the fitted model was performed using the Breusch-Godfrey test. The residuals seemed to be uncorrelated since the *p*-value was 0.9629 at more than a 5% significance level. However, the ARCH-LM test with the *p*-value of 0.0076 which was applied to the squared of residuals of the fitted VAR model, had rejected the null hypothesis of no ARCH effect in the residuals. This is because the *p*-value is less than a 5% significance level. This result indicated the existence of the heteroscedasticity effect in the residual.

Table 5.9 Residual analysis.

Adequacy checking	Test	Test statistics (*p*-value)
VAR-GARCH		
Autocorrelation	Breusch-Godfrey	0.3017 (0.1571)
Heteroscedasticity	ARCH-LM	1.143 (0.5615)
VAR-EWMA		
Autocorrelation	Breusch-Godfrey	0.3178 (0.1571)
Heteroscedasticity	ARCH-LM	1.336 (0.5092)
VAR-GO-GARCH		
Autocorrelation	Breusch-Godfrey	0.3117 (1.1474)
Heteroscedasticity	ARCH-LM	1.3434 (0.4655)
VAR(2)-fGARCH		
Autocorrelation	Breusch-Godfrey	0.2927 (0.1154)
Heteroscedasticity	ARCH-LM	1.034 (0.4385)
VAR(6)-GARCH		
Autocorrelation	Breusch-Godfrey	0.4121 (0.1778)
Heteroscedasticity	ARCH-LM	1.187 (0.5453)
VAR(6)-EWMA		
Autocorrelation	Breusch-Godfrey	0.3651 (0.1971)
Heteroscedasticity	ARCH-LM	1.564 (0.5231)
VAR(6)-GO-GARCH		
Autocorrelation	Breusch-Godfrey	0.3436 (0.1871)
Heteroscedasticity	ARCH-LM	1.451 (0.5522)
VAR(6)-fGARCH		
Autocorrelation	Breusch-Godfrey	0.3821 (0.1321)
Heteroscedasticity	ARCH-LM	1.093 (0.5125)

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Models Comparison

The comparison of the in-sample and out-sample performances of the VAR-GARCH, VAR-EWMA, VAR-Go-GARCH, and VAR-fGARCH model and VAR-fGARCH model. Table 5.10 presents the results of cross-validation analysis using MAPE, MAE, and RMSE, respectively. According to Lewis (1982), MAPE percentage error can be categories into three segments. MAPE error between 20 % to 50 % is in the "reasonable" forecasting power category, 10 % to 20 % in the "good" category, and less than 10 % is in the "excellent" category (Hsu and Wang, 2009). From Table 5.15, it can be seen that the proposed model, VAR-GARCH family model's ability to forecast (out-sample) the tax revenue data series falls into the "excellent" category of forecasting power. The smaller values for each in-sample and out-sample are in bold. Meanwhile VAR-fGARCH model yield the minimum error amongst the models, which is the best model.

Table 5.10 Cross-validation analysis.

Model	MAPE	MAE	RMSE
In-sample			
VAR(2)-Garch	0.5432	22.8923	22.8977
VAR(2)-EWMA	0.5619	22.2717	28.2928
VAR(2)-GO-GARCH	0.4029	21.8973	21.8974
VAR(2)-fGARCH	0.3944	15.828	20.3997
Out-sample			
VAR(2)-GARCH	0.2732	23.4365	23.4367
VAR(2)-EWMA	0.2422	22.8691	22.8691
VAR(2)-GO-GARCH	0.1954	20.9867	20.9868
VAR(2)-fGARCH	0.1251	11.8767	13.8901
In-sample			
VAR(6)-GARCH	0.5954	22.9856	22.9888
VAR(6)-EWMA	0.5792	22.3034	22.3075
VAR(6)-GO-GARCH	0.4551	21.9932	21.9984
VAR(6)-fGARCH	0.43454	15.899	20.5455
Out-sample			
VAR(6)-GARCH	0.2991	23.8768	23.8798
VAR(6)-EWMA	0.2244	22.6741	22.6777
VAR(6)-GO-GARCH	0.2131	20.9957	20.9991

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VAR(6)-fGARCH	0.1653	11.9934	13.9789

Conclusion

Tax revenue challenges as been come critical issues due to a significant number of financial crises that smash the global economy. Recently in Nigeria, there are extensive, unusual, and persistent financial crises (economic recession) and the falling price of crude oil at the international market particularly the state with a low and poor source of revenue and other factors.

In the real essence the study on modeling and forecasting future tax revenue challenges for good planning to withstand such economic crises. Modelling multivariate financial (tax revenue) parameters is vital in analyzing future economic indices. However, multivariate financial time series were characterized by variance volatility

References

Adammer, P., Bohl, M. T., & Ledebur, E.-O. von. (2016). Dynamics Between North American And European Agricultural Futures Prices During Turmoil And Financialization. *Bulletin of Economic Research*

Ashwani, K., Kapil, K., Naresh, K., Satyawati, S., & Saroj, M. (2010). Renewable energy in India: Current status and future potentials. *Renewable and Sustainable Energy Reviews, 14*, 2434–2442

Ayele, A. W., Gabreyohannes, E., & Tesfay, Y. Y. (2017). Macroeconomic determinants of volatility for the gold price in Ethiopia: the application of GARCH and EWMA volatility models. *Global Business Review*, *18*(2), 308-326.

Boussama, F., Fuchs, F., & Stelzer, R. (2011). Stationarity and geometric ergodicity of BEKK multivariate GARCH models. *Stochastic Processes and Their Applications,* 121(10), 2331-2360. http://doi.org/10.1016/j.spa.2011.06.001

Chung, S. L., Hung, C. H., & Yeh, C. Y. (2012). When does investor sentiment predict stock returns?. *Journal of Empirical Finance*, *19*(2), 217-240.

El Hedi Arouri, M., Lahiani, A., & Nguyen, D. K. (2015). World gold prices and stock returns in China: Insights for hedging and diversification strategies. *Economic Modelling, 44,* 273-282. http://doi.org/10.1016/j.econmod.2014.10.030

Fan, J., Wang, M., & Yao, Q. (2008). Modelling multivariate volatilities via conditionally uncorrelated components. *Journal of the Royal Statistical Society: series B (statistical methodology)*, *70*(4), 679-702.

Halkos, G. E., & Tsirivis, A. S. (2019). Effective energy commodity risk management: Econometric modeling of price volatility. *Economic Analysis and Policy*, *63*, 234-250.

Hsu, L. C., & Wang, C. H. (2009). Forecasting integrated circuit output using multivariate grey model and grey relational analysis. *Expert systems with applications*, *36*(2), 1403-1409..

Kumar, M. (2013), "Returns and volatility spillover between stock prices and exchange rates: empirical evidence from IBSA countries", International Journal of Emerging Markets, Vol. 8 No. 2, pp. 108-128.

Lewis, C. D. (1982). Industrial and business forecasting methods: A practical guide to exponential smoothing and curve fitting. Butterworth-Heinemann.

MacDonald, R., Sogiakas, V. and Tsopanakis, A. (2018), "Volatility co-movements and spillover effects within the eurozone economies: a multivariate GARCH approach using the financial stress index", Journal of International Financial Markets, Institutions, and Money, Vol. 52, pp. 17-36.

Morema, K., & Bonga-Bonga, L. (2020). The impact of oil and gold price fluctuations on the South African equity market: Volatility spillovers and fiscal policy implications. *Resources Policy*, *68*, 101740.

Norrulashikin S.M, Fadhilah B.Y., Ibrahim L.K., (2018) Performance Evaluation of a New Hybrid Multivariate Meteorological Model Analysis: A Simulation Study Malaysian Journal of Industrial and Applied Mathematics; 2018 - matematika. UTM.my https://doi.org/10.11113/matematika.v34.n1.1026

Park, B. U., Simar, L., & Zelenyuk, V. (2017). Nonparametric estimation of dynamic discrete choice models for time series data. *Computational Statistics & Data Analysis*, *108*, 97-120.

Sadorsky, P. (2014). Modeling volatility and conditional correlations between socially responsible investments, gold and oil. *Economic Modelling, 38,* 609618. http://doi.org/10.1016/j.econmod.2014.02.013

Živkov, D., Manić, S., & Đurašković, J. (2020). Short and long-term volatility transmission from oil to agricultural commodities–The robust quantile regression approach. *Borsa Istanbul Review*, *20*, S11-S25.

Zhuang, X.-F., & Chan, L.-W. (2004). Volatility Forecasts in Financial Time Series with HMM-GARCH Models. Intelligent Data Engineering and Automated Learning – IDEAL 2004, 807–812. doi:10.1007/978-3-540-28651-6_120

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