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Evaluating Combine White Noise with US and UK GDP Quarterly Data

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ABSTRACT

The main objective of this study is to evaluate the Combine White Noise (CWN) model, for the confirmation of its effectiveness in addressing the error term challenges of the data that exhibits heteroscedasticity. CWN models the leverage effect appropriately with better estimation results of which the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model cannot handled. The determinant of the residual covariance matrix values indicates that CWN estimation is efficient for each country. Every country has a minimum forecast errors of CWN estimation which is an indication of forecast accuracy. The overall results indicate that CWN estimation provide more efficient and better forecast accuracy than EGARCH estimation. This boosts the economy of the nation.

Keywords: *Combine white noise; Efficient; Forecast accuracy; Log likelihood.*

1. INTRODUCTION

The error term constitute the missing variables, error in variables and simultaneous causality mostly, in data analysis [1]. The error term elements with high frequency data and large data size make it hard to find an accurate model as the data period increases [1].Researchers have been advocating for models at different time to overcome this challenge, which actually have efficient estimation for sometimes. The large data size and high data frequency determine the suitable model at a particular time[2-10]. The challenges of not modeling the error terms efficiently by the existing models are dealt with by using Combine White Noise (CWN) approach [7, 11, 12, 13]. In this study, the CWN model is employed to carry out the empirical analysis, to show its effectiveness in modeling the error terms appropriately [14].

In stochastic time series analysis, error term has been revealed in structural simultaneous system of equations by Cowles researchers group [15]. The computer advancement and simultaneous equations models are

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growing in size, these make the simultaneous equations models perform poorly [15, 16, 17].

The simultaneous system of equations procedures for macroeconomic variable is weak in estimation, because the error term is unsuitably evaluated[18].

Therefore, Sims [18] comes up with vector autoregressive (VAR) model to uplift the weaknesses of simultaneous system of equations. VARs come with tools that are simple for estimation, structure inference and forecasting, that aids in policy making. VAR modeled the error term which is white noise effectively. When the data analysis exhibit heteroscedastic error term, the VAR white noise cannot model the unequal variances (heteroscedastic error term), VAR can only model error term that exhibit equal variances (white noise)[2, 3, 4, 19].

Engle [5] overcomes the heteroscedastic error term by introducing Autoregressive Conditional Heteroscedasticity (ARCH) model. ARCH models grasp group errors effectively and able to accomplish suitable forecast variances. ARCH models with large length lag structure will have estimation problem with negative variance parameters. While ARCH can only handle fixed lag length with reasonable estimation.

Bollerslev [6] employs generalized ARCH model to allow large lag length structure, however, it has thick tails challenges when modeling the high frequency data distribution of the stochastic time series. Bollerslev [20] captures thick tails challenge by employing student's t-distribution to tackle the thick tail in the distribution.

Engle [5] and Bollerslev [6] neglect the volatility that affects the direction of return, but focus on the magnitude of returns of the conditional variance [3, 7, 9]. [10, 11] reveal the GARCH weakness in modeling the excess Kurtosis and volatility persistence.This motivated the GARCH family. A reaction to news is a shock which is the volatility. The examination of news timing can boost the usual volatility mechanism, like economic speculations that are not the characteristics of a shock [8].

Integrated GARCH model is comparable with ARIMA (0, 1, 1) model in terms of the definition of an ACF of squared variables, if the variables exhibit integrated of order one and are stationary in first difference, in that case, it is known as IGARCH. Exponential GARCH captures the conditional variance persistence measurement challenges[3].

Threshold GARCH (TGARCH) and exponential GARCH (EGARCH) uplift the effects of positive and negative shocks of asymmetric on the same dimension of conditional volatility in a variety of techniques. Leverage is a particular case of asymmetry. To solve asymmetry challenges, positivity restriction are imposed on the parameters of the EGARCH model [7, 11, 12, 13, 22].

It has been established that positive shocks may have less impact on volatility than the negative shocks of the same magnitudes. Since both the positive and negative shocks obtain equal degree of importance in GARCH model, which cannot take care of leverage effect [7, 11, 12, 13]. Nelson [11] introduces the EGARCH to capture the leverage effect, although it can only capture the asymmetric volatility. While a negative shock enlarges the volatility with the coefficient of the conditional variance being negative. The positivity restriction positioned on each conditional variance follows the simple GARCH specification and the conditional variance without restriction necessitates the conditional volatility to be negative. Modeling leverage effect is not possible in EGARCH as there are no general statistical properties to estimate the EGARCH parameters [12, 13].

The purpose of this study is to model the E(GARCH) errors with EGARCH and Combine White Noise (CWN) with two different data of two countries. Modeling each country data at a time and compare the results of EGARCH estimation and CWN estimation is to have a reliable estimation and forecasting accuracy to boost the economy.

2. MATERIALSAND METHODS

The data of U.S. and U.K. Real Gross Domestic Product (GDP) quarterly data from 1960 to 2014 are obtained from the DataStream of Universiti Utara Malaysia library for the verification of the effectiveness of Combine White Noise model.

Consider the autoregression model

$$y_t = \phi y_{t-1} + \varepsilon_t, \quad (2.1)$$

Permit the stochastic approach of a real-valued time to be ε_t, and the complete information through *t* time is I. The GARCH model is

$$\varepsilon_t \mid \mathrm{I}_{t-1} \sim \mathrm{N}(0, h_t), \quad (2.2)$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$

$$= \omega + A(L)\varepsilon_t^2 + B(L)h_t \quad (2.3)$$

The EGARCH specification is

$$\log h_t = \alpha + \beta \mid z_{t-1} \mid + \delta z_{t-1} + \gamma \log h_{t-1}, \quad \mid \gamma \mid < 1 \quad (2.4)$$

where $z_t = \varepsilon_t / \sqrt{h_t}$ is the standardized shocks, $z_t \sim iid(0, \alpha)$. $\mid \gamma \mid < 1$ is when there is stability. The impact is asymmetric if $\delta \neq 0,$ although, there is existence of leverage if $\delta < 0 \;\; and \;\; \delta < \beta < -\delta.$ While both β and δ must be positive which the variances of two stochastic processes are, then, modeling leverage effect is not possible [12, 13].

The unequal variances (heteroscedastic errors) behaviors in the process of estimation being exhibited by GARCH models can be simplified into Combine

White Noise models. The standardized residuals of GARCH errors which are unequal variances are decomposed into equal variances (white noise) in series to deal with the heteroscedasticity. The regression model is employed to transform each equal variances series to model.

Moving average process is employed for the estimation of these white noise series which is called Combine White Noise.

$$Y_1 = \varepsilon_{1t} + \theta_{11}\varepsilon_{1,t-1} + \theta_{12}\varepsilon_{1,t-2} + \ldots\theta_{jq}\varepsilon_{j,t-q}$$

$$Y_2 = \varepsilon_{2t} + \Phi_{21}\varepsilon_{2,t-1} + \Phi_{22}\varepsilon_{2,t-2} + \ldots\Phi_{jq}\varepsilon_{j,t-q}$$

$$\vdots \qquad .$$

$$Yj = \varepsilon_{jt} + \phi_{j1}\varepsilon_{j,t-1} + \phi_{j2}\varepsilon_{j,t-2} + \ldots\phi_{jq}\varepsilon_{j,t-q}$$

$$Y_{jt} = \sum_{j=1}^{q}\theta_j\varepsilon_{j,t-q} + \sum_{j=1}^{q}\Phi_j\varepsilon_{j,t-q} + \ldots\sum_{j=1}^{q}\phi_j\varepsilon_{j,t-q} \quad (2.5)$$

$$= A(L)\varepsilon_t + B(L)\varepsilon_t + \ldots$$

$$= \varepsilon_t[A(L) + B(L) + \ldots] \quad (2.6)$$

$$= Q\varepsilon_t \quad (2.7)$$

$$= U_t ,$$

It can be written as

$$Y_t = U_t , (U_t \sim \mathrm{N}(0, \sigma_c^2) \quad (2.8)$$

where A(L) + B(L) + … = Q which are the matrix polynomial, U_t is the error term of combine white noise model and σ_c^2 is the combination of equal variances.

The combine variances of the combine white noise is

$$\sigma_c^2 = \sigma_1^2 + \sigma_2^2 + \ldots \quad (2.9)$$

Considering the best two variances in the best two models produced by the Bayesian model averaging output. The combine variance follows:

$$\sigma_c^2 = \sigma_1^2 + \sigma_2^2 \quad (3.0)$$

The variance of errors, σ_c^2 in the combine white noise can be written:

$$\sigma_c^2 = W^2\sigma_1^2 + (1-W)^2\sigma_2^2 + 2\rho W\sigma_1(1-W)\sigma_2$$
(3.1)

where the balanced weight specified for the model is *W*. The least of σ_c^2 appearing, when the equation is differentiated with respect to *W* and equate to zero, obtaining:

$$W = \frac{\sigma_c^2 - \rho\sigma_1\sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2} \quad (3.2)$$

Where ρ is the correlation; intra-class correlation coefficient is used for a reliable.

3. RESULTS AND DISCUSSION

The time plot of the data for both U.S. GDP and U.K. GDP showed upward trend which were the behavior of non-stationary series.

The data of U.S and U.K. GDP were transformed in returns series to observe the volatility clustering, long tail skewness and excess kurtosis which have been the characteristics of heteroscedasticity. There were exhibition of volatility with unequal variances shown in the graphs.

In table 1 U.S. data reported that, there was left long tail skewness, excess kurtosis and Jarque-Bera test was significant that was an indication of non-normality with standard deviation less than one. In table 1 also U.K. data reported that, there was right tail skewness, excess kurtosis and Jarque-Bera test was highly significant that was an indication of non-normality with standard deviation less than one.

The U.K. data distribution was very close to one compared to U.S. data distribution. U.S. data distribution was skewness to the left while U.K. data distribution was to the right. The kurtosis was higher in data distribution of U.K.

Table 1 equally showed that the ARCH LM tests for the effect of heteroscedasticity in the data series; F-Statistic and Obs*R-squared were significant that was an indication of ARCH presence in the data in both U.S. and U.K. data distribution. U.K. ARCH presence in the data was higher than the U.S. data distribution. The ARCH effect was more in U.K. data distribution.

Table 1 Histogram-normality and ARCH tests for U.S. and U.K. EGARCH data

	Coefficient/value U.S. data	probability	Coefficient/value U.K. data	probability
Normal test				
Standard deviation	0.840452		0.966867	
Skewness	-0.320441		0.375454	
Kurtosis	4.515921		7.014953	
Jarque-Bera	24.71731	0.000004	152.2389	0.000000
ARCH tests				
F-Statistic	1.372665	0.0027	0.060187	0.0064
Obs*R-squared	1.376645	0.0007	0.060730	0.0053

Tables 2A and 2B showed that the AIC, BIC and HQ minimum information criteria with log-likelihood that were used to select the appropriate model between ARCH and GARCH family models. EGARCH model was choosing because it had minimum values of AIC, BIC and HQ with high log-likelihood values. U.S. data estimation had minimum information criteria and high log likelihood, when compared with U.K. data estimation for ARCH and GARCH estimation.

In tables 2A and 2B the CWN had the minimum information criteria with high log likelihood. The CWN estimation gave better results with minimum information criteria and high log likelihood when compared with EGARCH estimation. The CWN in table 2B for U.K. data had minimum information criteria and high log likelihood when compared with U.S. data estimation in table 2A.

Table 2A U.S. data ARCH, GARCH and CWN models coefficients, information criteria and log likelihood values

	α	β	δ	γ	AIC	BIC	HQ	LL
ARCH	0.37700	0.14103			2.30379	2.42799	2.35396	-243.11
	(0.0000)	(0.0000)						
EGARCH	0.32771	0.32056	-0.0656	0.89149	2.26776	2.37644	2.35396	-240.19
	(0.0000)	(0.0160)	(0.3970)	(0.0000)				
CWN					-0.5235	-0.4306		63.32035

Note: α is the coefficient of the mean equation, β and δ are the coefficients of the variance equations, while γ is the coefficient of the log of variance equation. In the parentheses is the Probability Value (PV)

Table 2B .U.K. data ARCH, GARCH and CWN models coefficients, information criteria and log likelihood values

	α	β	δ	γ	AIC	BIC	HQ	LL
ARCH	0.334938	0.424743			2.68436	2.74646	2.70944	-288.60
	(0.0003)	(0.0000)						
EGARCH	0.291288	0.218189	0.09329	0.98997	2.35147	2.37644	2.46014	-249.31
	(0.0000)	(0.0106)	(0.1228)	(0.0000)				
CWN					-0.4444	-3.3515		383.158

Note: α is the coefficient of the mean equation, β and δ are the coefficients of the variance equations, while γ is the coefficient of the log of variance equation. In the parentheses is the Probability Value (PV)

In EGARCH modeling, the leverage is not possible because any restriction imposed will be positivity restriction which has no leverage effect [12, 13].No proposition has removed heteroscedasticity completely [2, 23, 24]

To avoid the above challenges, the standardized residuals graph of the EGARCH model (GARCH errors) with unequal variances and zero mean were decomposed into equal variances series (white noise series). There were some graphs of equal variances (white noise series) with mean zero being obtained from graph of GARCH errors. These white noise series were fitted into regression model to make each a model.

The implementation of Bayesian model averaging produced two best models from the first best models [25]. For confirmations, fitting linear regression with autoregressive errors, 220 was the number of observation, with zero mean and variance one [26]. Therefore, the best two models were the white noise models.

Tables 3A and 3B indicated that independent samples test were conducted to test whether data set of the two white noise models have equal variances or not. The test in Table 3A for U.S. data revealed that the variability in the distribution of the data was no significantly different value which was greater than the p-value 0.05. Hence, the model had equal variances. Table 3B for U.K. data revealed that the variability in the distribution of the data was significantly different value which was less than the p-value 0.05. Hence, the model had unequal variances[27, 28, 29].

Table 3A. Levene’s test for equal variances for U.S. data

	Independent samples test								
	Levene's test for equality of variances		t-test for equality of means					95% Confidence interval of the difference	
	F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std.Error	Lower	Upper
B Equal variances assumed	1.414	0.235	2.159	438	0.031	0.05909	0.02737	0.0053	0.11288
Equal variances not assumed			2.159	255.236	0.032	0.05909	0.02737	0.00519	0.11299

Table 3B. Levene’s test for equal variances for U.K. data

	Independent samples test								
	Levene's test for equality of variances		t-test for equality of means					95% Confidence interval of the difference	
	F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std.Error	Lower	Upper
B Equal variances assumed	5.504	0.019	1.133	438	0.258	0.01545	0.01364	-0.01135	0.04226
Equal variances not assumed			1.133	255.502	0.258	0.01545	0.01364	-0.01140	0.04231

Table 4 revealed for both U.S. and U.K. data estimation that CWN appeared to be more appropriate model for estimation and forecasting, when comparing with EGARCH models. In U.K. CWN and EGARCH had minimum values of root mean square error (RMSE) and mean absolute error (MAE) with high mean absolute percentage error (MAPE) when comparing with U.S. forecast errors.

Table 4 The summary of GARCH and CWN models estimation and forecasting evaluation for U.S. and U.K. data set

	CWN	GARCH	CWN	GARCH
	U.S. data		U.K. data	
Estimation residual diagnostic				
Stability Test (Lag structure)	Stable	Stable	Stable	Stable
Correlogram (square) residual	covariance stationary	Stationary	covariance stationary	Stationary
Portmanteau Tests	No autocorrelation	No autocorrelation	No autocorrelation	No autocorrelation
Histogram-Normality Tests	Not normal	Not Normal	Not normal	Not normal
ARCH Test	No ARCH effect	No ARCH effect	No ARCH effect	No ARCH effect
Dynamic forecast evaluation				
RMSE	0.482821	627.8018	0.167297	0.653369
MAE	0.113995	439.1633	0.040005	0.408789
MAPE	1.387052	2.980324	1.427953	169.7009
Residual diagnostic				
Correlogram (square) residual	Stationary	Stationary	Stationary	Stationary
Histogram-Normality Tests	Not normal	Not normal	Not normal	Almost normal
Serial Correlation LM Tests	No serial correlation	No serial correlation	No serial correlation	No serial correlation
Heteroscedasticity Test	No ARCH effect	No ARCH effect	No ARCH effect	No ARCH effect
Stability diagnostic				
Ramsey reset tests	Stable	Stable	Stable	Stable
Determinant residual covariance	0.001923		0.000104	

4. CONCLUSION

The CWN model has proved to be more efficient and uplifts EGARCH weaknesses. CWN estimation passes stability condition, stationary, serial correlation, the ARCH effect tests and it also passes the Levene's test of equal variances using U.S. data. While CWN estimation passes stability condition, stationary, serial correlation, the ARCH effect tests and fails the Levene's test of equal variances using U.K. data.

The CWN estimation yield better results with minimum information criteria and high log likelihood values in both U.S. and U.K. data estimation comparing with EGARCH information criteria and log likelihood values. The results of CWN estimation of U.S. data is better when compare with the U.K. CWN estimation results.

CWN has the minimum forecast errors which are indications of better results when compare with the EGARCH model dynamic evaluation forecast errors in both U.S. and U.K. data forecast evaluation ([19, 30, 31]. In U.K. CWN has minimum of root mean squared error and mean absolute errors of forecast but high mean absolute percentage errors comparing with U.S. forecast errors.

The determinants of the residual of covariance matrix values indicate that CWN estimationis efficient in the two countries. In CWN estimation, the determinant of the residual of covariance matrix value for U.K. is more efficient than the U.S.

Based on every result in the empirical analysis of the two countries, CWN is more appropriate model for empirical analysis. For this reason, CWN is recommended for modeling the data that exhibits conditional heteroscedasticity and leverage effect.

The contribution of this study to the scientific community is that the CWN uplifts the weaknesses of the existing models and improves the forecast accuracy. CWN estimation efficiency and forecast output is more reasonable for policy making. This will boost the economy of the nation.

CONFLICT OF INTEREST

No conflict of interest was declared by the authors.

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