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MODELLING EXCHANGE-RATE VOLATILITY WITH COMMODITY PRICES

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Johns Hopkins Institute for Applied Economics,
Global Health, and the Study of Business Enterprise

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About the Series

The *Studies in Applied Economics* series is under the general direction of Professor Steve H. Hanke, Founder and Co-Director of the Johns Hopkins Institute for Applied Economics, Global Health, and the Study of Business Enterprise (hanke@jhu.edu).

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Abstract

This paper estimates a model of exchange-rate volatility that includes commodity prices as an exogenous determinant. We apply this model to the mining-based economy of Suriname. Fluctuations of the exchange rate are detrimental for the economy. This was evident in 2015 and 2016 when the economy of Suriname considerably contracted due to persistent negative commodity price shocks. First, we calibrate higher order General Autoregressive Conditional Heteroscedastic (GARCH) models to model the conditional variances of the exchange rate with available monthly data for the period 1994 to 2019. We obtained useful results from Exponential, Asymmetric, Threshold, Component and combined Mean-GARCH models calibrated with standardized error distributions. Then, we perform in-sample forecasts with the calibrated models for the period 2012 to 2019. Lastly, we select the best-performing models to forecast conditional variances of the exchange rate.

Keywords: Exchange Rate Volatility, GARCH models, Heteroscedasticity
JEL codes: C52, E44 44, E47

1. Background

Calvo and Reinhart (2002) show that, over the last few decades, many countries have adopted floating exchange rate regimes. A floating exchange rate is regarded as an automatic stabilizer for rebalancing the economy. On the contrary, many countries are reluctant to adopt a floating exchange rate regime because of inflationary pressures and financial sector vulnerability. Suriname is among the countries that adopted a free-floating exchange rate regime, namely in 2016. This empirical analysis draws useful insights from Abdullah et al (2017) and Weber (2019). Abdullah et al (2017) model and forecast conditional exchange rate volatility (ERV) in Bangladesh using GARCH models. Weber (2019) analyzes the effects of Central Bank Transparency (CBT) on ERV. According to Weber (2019), CBT, which is largely associated with central bank forecasts and communication, is a determinant of ERV in developed economies. For developing economies, the effects are small, and for small less-developed economies, the effects are less clear.

Prolonged ERV imperils steady growth of less developed economies, see Arize et al. (2000), Belke and Gros (2002), Servén (2003), Bagella et al. (2006), Aghion et al. (2009)[1]. One of the main causes of ERV is prevailing uncertainty of monetary policy (Mussa, 1979). Bouakez and Normandin (2010) analyze the effects of monetary policy on the exchange rates of six economies with the U.S. as the main trading partner. They found that monetary policy shocks account for around 40% of ERV. Those studies mentioned earlier indicate the economic importance of ERV, the causes and consequences of ERV and the role of monetary policy.[2]

[1] These studies show the effects of ERV on trade, investment, labor productivity, and GDP growth.
[2] According to IMF (2009), there are roughly three type of exchange rate arrangements: hard pegs, soft pegs and floats. Within these categories, breakdowns that are more possible are available. Hard pegs refer to exchange rate arrangements with no separate legal tender as well as currency boards. The pool of soft pegs contains conventional pegged arrangements, stabilized arrangements, crawling pegs, Crawl-like arrangements, and pegged exchange rates with horizontal bands. Floating arrangements: floating and free floating.

In this paper, we model and forecast conditional variances of the ER using higher-order GARCH models.[3] To the best of our knowledge, no study is conducted on this topic for Suriname. As the ER is time varying, more accurate forecast intervals can be obtained by modelling the variances of the error terms. Macroeconomic time series exhibit phases of relative tranquility followed by periods of high volatility, known as volatility clustering. Section 2 presents the literature review, while section 3 presents the methodology. Section 4 explains the estimation results and compares different GARCH models and forecast accuracy. Finally, section 5 serves as the conclusion.

2. Literature Review

Exchange rate volatility

Frenkel (1981) argues that exchange rates are affected by anticipated and unanticipated events. The anticipated events are associated with common knowledge, while the unanticipated events comprise new information. Ehrmann and Fratzscher (2005) use real-time data to investigate ERV. The study shows that exchange rates respond strongly to news in periods of market uncertainty and large shocks. Melvin and Yin (2000) and Dominguez and Panthaki (2006) show that news influences ERV when more news is broadcasted in times of uncertainty. According to Evans and Lyons (2005), ERs do not adjust to news immediately but rather take time because opinions across markets vary strongly. Love and Payne (2008) examine three ERs (USD/EUR, GBP/EUR, and USD/GBP) and reveal that scheduled macroeconomic news may affect ERs. They argue that two-thirds of ER reactions to macroeconomic news relate to trade. Chen and Gau (2010) analyze the effects of scheduled macroeconomic announcements on spot and futures ERs. They show that announcements affect both types of ERs, causing volatility. Blinder et al. (2008) study the impact of CB communication on monetary policy. Their findings show that communication is a powerful instrument to enhance the predictability of monetary policy that affects ERs. Flood and Rose (1999) analyze the relationship between ERs and money, output, interest rates and shocks differentials. They argue that these variables greatly influence ERs. Moosa and Bhatti (2010) modified this model further by adding factor expectations.

[3] Modelling and forecasting volatility in financial markets is often carried out by GARCH models because of their ability to integrate often observed, stylized facts in financial data. Some stylized facts are: excess kurtosis, fat tails, non-normality, clustering of volatility, correlation of volatility, mean reversion (volatility often returns to its mean after periods of disruptions), information leverage effects, long memory or persistent volatility, and uncertainty in macroeconomic data implying volatility in financial data.

CBT is a key determinant of ER volatility. Weber (2019), for example, shows that CBs can reduce ER volatility by regularly publishing monetary policy stances and forecasts. These announcement affects market dynamics. Fujiwara (2005) provides evidence that the private sector tends to adjust its forecast based on the latest CB forecasts. Farka (2009) shows that an increase in CBT results in a better understanding of monetary policy and thus, may reduce future monetary policy surprises. On the other hand, Van der Cruijsen et al. (2010) and Weber (2019) show that volatility may increase because of increased CBT. For instance, more information provision could lead to more noise, resulting in changing expectations about future monetary policy stance. Cruijsen et al. (2010) shows that an optimum level of transparency improves private sector forecasts. However, beyond that optimum, agents attach too much weight to the conditionality of their forecast, leading to diversion. Overall, the effects of CBT on ERV in developed economies are thoroughly quantified through various econometric models. However, there is not much published research on this topic for small states.

GARCH Models

GARCH models are designed for modelling and forecasting conditional heteroscedasticity in financial data. Engle (1982) proposes the Auto Regressive Conditional Heteroscedasticity (ARCH) model to model heteroscedasticity instead of considering it as a problem that should be corrected. Bollerslev (1986) developed the GARCH model to capture different features of volatility in financial data. The ARCH model requires large lag length, which means it estimates a large number of parameters to predict volatility. The GARCH model allows conditional variance to depend upon its own lag, which means it reduces the number of required ARCH lags. Ramasamy and Munisamy (2012) argue that GARCH models are efficient for predicting volatility. Bollerslev (1987), Hsieh (1989) and Baillie and Bollerslev (1989b) find that fundamental GARCH models provide a good description for most exchange rate series under free floating regimes.

A number of extensions of the basic GARCH model have shown to improve modelling of many macroeconomic variables and, in particular, of financial variables. The types of GARCH model extensions are: exponential (EGARCH); asymmetric power (APARCH); threshold (TGARCH); integrated (IGARCH); and Component (CGARCH).

Nelson (1999) developed the EGARCH model to capture asymmetrical effects in financial data. Other authors such as Glosten, Jagannathan, Runkle (1993) utilize EGARCH to capture leverage effects, which are exponential rather than quadratic. They argued that the improvement made by leveraging in EGARCH did not improve forecasting accuracy compared to other GARCH-types models. Ding, Granger and Engel (1993) developed the APARCH model to capture higher order moments (volatility clustering). APARCH allows for a more general modelling of standard errors, which can be multiplied by a standard Gaussian distribution.[4] Zakoian et al. (1993) introduced the TGARCH to model both asymmetries and leverage effects.[5] Financial data often display persistent volatility. Engle and Bollerslev (1986) constructed the IGARCH to model persistent volatility.[6] The component (CGARCH) model developed by Engle and Lee (1999) accounts for long-run variance. Suppose that the volatility process has a unit root (or is highly persistent), this indicates that there may be a stochastic (permanent trend) component and a transitory component. The constant volatility to which the conditional variance is assumed to mean-revert in the GARCH model, is time varying. Decomposing the conditional variance in a permanent and transitory component is a way to investigate long-run and short-run volatility movements, which are forecastable.

3. Data and Methodology

We model the conditional heteroscedasticity of the ER of Suriname (the nominal exchange rate of the SRD/USD) as a dependent variable. The variance regressor is the West Texas Intermediate oil price.[7] These are two key macroeconomic indicators for the mining-based Surinamese

[4] Tse (1998) and Pelinescu (2014) examine the conditional heteroscedasticity of ERV using APARCH models. According to Tse, the results obtained from the APARCH model showed no substantial difference with the other GARCH models. Pelinescu concluded that the ERs consisted of ARCH processes and ER returns were correlated with volatility, rendering the APARCH a useful model.

[5] For stocks, there is a strong negative correlation between current returns and future volatility. Volatility declines when returns increase and rises when returns fall. This is known as the leverage effect. For example, “bad” news seem to have a more pronounced impact on volatility than “good” news.

[6] Dhamija and Bhalla (2010) show that IGARCH and TGARCH models performed well when forecasting ERV with daily observations (British pound, German mark, Japanese yen, Indian rupee and Euro).

[7] The WTI is the benchmark price for the local oil-producing company (Staatsolie). We utilize this conditional variance regressor for two reasons. First, Suriname is a net exporter of oil. Persistent volatility in oil price affects state revenues from the oil industry. At the same time, foreign exchange is required to finance the import of oil. For a mining-based economy like Suriname’s, modelling and forecasting ER with oil price as the variance regressor is necessary to understand dynamics of exchange rate.

economy. The data set contains monthly observations for 1994m1-2019m11 of the Central Bank of Suriname and the World Bank. Since the nominal exchange rate series are nonstationary, we converted the series into the rate of return on the exchange rate by following logarithmic transformation:

$$r_t = \ln\left(\frac{fx_t}{fx_{t-1}}\right)$$

r_t stands for exchange rate return in period t, fx_t and fx_{t-1} are the nominal exchange rate of the SRD/USD in period t and $t-1$.

Specification of different ARCH/GARCH Models

GARCH(1,1) model:

$$\text{Mean: } y_t = \beta x_t + \varepsilon_t \quad (1)$$

$$\text{Variance: } \sigma_t^2 = \alpha + \gamma\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2 \quad (2)$$

Where y_t is the dependent variable; x_t is an independent/exogenous variable; σ_t^2 is the conditional variance; ε_{t-1}^2 is the ARCH term; σ_{t-1}^2 is the GARCH term.[8] If GARCH models are estimated using a long time-series model, then the sum of ARCH and GARCH terms are close to unity.

A more generalized ARCH model is the GARCH (p, q) model:

$$\text{Variance equation: } \sigma^2{}_t = \alpha + \sum_{i=1}^{q}\gamma_i\varepsilon^2{}_{t-i} + \sum_{j=1}^{p}\theta_j\,\sigma^2{}_{t-j} \quad (3)$$

Conditional variance in the mean equation (GARCH-M) is specified as:

$$\text{Mean: } y_t = \beta x_t + \varphi\sigma^2{}_t + \varepsilon_t \quad (4)$$

The conditional mean in the model is implemented by standard deviation, variance and log-variance. The GARCH-M(1,1) means that the conditional mean depends on the conditional volatility.

[8] This term is zero in an ARCH specification.

TGARCH model specification.

$$\sigma^2{}_t = \alpha + \sum_{j=1}^{p} \theta_j \sigma^2{}_{t-j} + \sum_{i=1}^{q} \gamma_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \delta_k \varepsilon_{t-i}^2 * I_{t-k} \tag{5}$$

If I_{t-k} = 0, then there is no leverage effect. If the parameter is different from 0 then there is leverage effect.

EGARCH model.

$$\log(\sigma^2{}_t) = \alpha + \sum_{j=1}^{p} \theta_j \log\left(\sigma^2{}_{t-j}\right) + \sum_{i=1}^{q} \gamma_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{r} \delta_i \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \tag{6}$$

Since the right-hand side variable is the log of conditional variance, EGARCH models imply that the leverage effect is exponential rather than quadratic.

IGARCH model.

$$\sigma^2{}_t = \alpha + \beta_1 \varepsilon_{t-1}^2 + (1 - \beta_1) a_{t-1}^2 \tag{7}$$

The right-hand variable, $(1 - \beta_1)a_{t-1}^2$, captures the persistency in financial data.

ARCH (PARCH) model.

$$\sigma^{\boldsymbol{\delta}}{}_t = \omega + \sum_{j=1}^{p} \theta_j \sigma^{\boldsymbol{\delta}}{}_{t-j} + \sum_{i=1}^{q} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-1}) \delta \tag{8}$$

δ, the long-run coefficient, is estimated. Note that the standard GARCH model is nested as a special case of the more general PARCH model when δ=2 and $\gamma_i = 0$. As in previous cases, asymmetric effects are present if $\gamma_i \neq 0$.

CGARCH model.

$$\delta_t^2 = \alpha(\varepsilon_{t-1}^2 - \delta_{t-1}^2) + \beta(\sigma_{t-1}^2 - \delta_{t-1}^2) \tag{9}$$

The first part of the equation estimates the long-run trend component and the second part estimates the transitory component. The long-run variance is parameterized by the equation

$$\delta_t^2 = \omega + \rho(\delta_{t-1}^2) + \varphi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \tag{10}$$

Model evaluations

We apply three error measures to evaluate the forecasting performance of the forecasting models.

Root Mean Square Error (RMSE):

$$\sqrt{\sum_{t=T+1}^{T+h} (\hat{y}_t - y_t)^2} \ /h \tag{11}$$

Where y_t is the actual observed value and $\hat{y}$ is the fitted value in time *t*.

Mean Absolute Error (MAE):

$$\sum_{t=T+1}^{T+h} |\hat{y}_t - y_t|/h \tag{12}$$

Theil-U Statistics:

$$\frac{\sqrt{\sum_{t=T+1}^{T+h} (\hat{y}_t - y_t)^2/h}}{\frac{\sqrt{\sum_{t=T+1}^{T+h} \hat{y}_t{}^2}}{h} + \frac{\sqrt{\sum_{t=T+1}^{T+h} y_t{}^2}}{h}} \tag{13}$$

Error Distribution

GARCH models are calibrated with three standardized distributions of residuals. The assumptions may follow a Normal Gaussian distribution, a Student's *t*-distribution, and a Generalized Error Distribution (GED). The calibration and adequacy of GARCH models depend on these distributions. Our literature survey shows that the vast majority of GARCH models are calibrated with a normal Gaussian distribution and a Student's *t*-distribution of residuals. We calibrate higher order GARCH models with all three distribution assumptions and select the adequate models to perform in-sample forecasts.

4. Results

Tables 1 to 3 present the results of calibrated GARCH models with the Normal Gaussian distribution, the Student's *t*-distribution, and the GED. Table 4 compares the accuracy of the calibrated GARCH models while table 5 presents the in-sample forecast accuracy statistics. The in-sample forecast is conducted for the period 2012m1-2019m11.

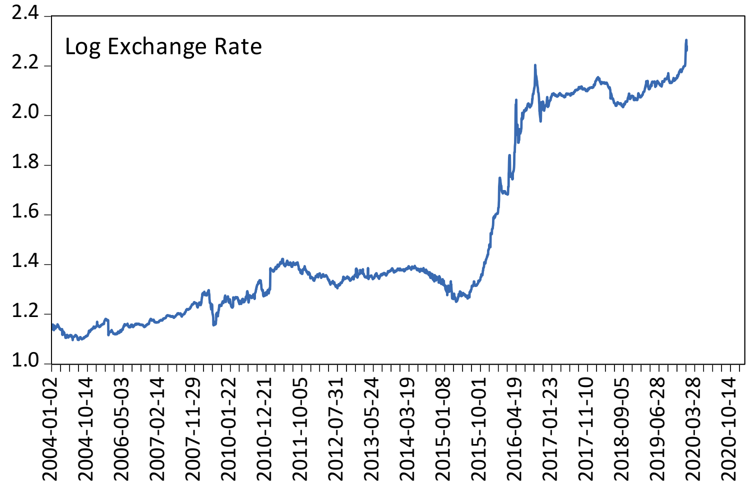

Figure 1. Evolution of Exchange Rate

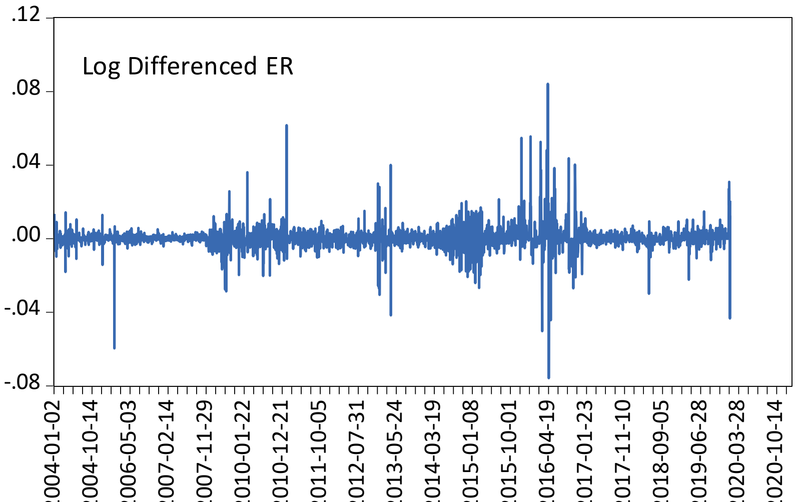

Figure 2. Volatility in Log Exchange Rate

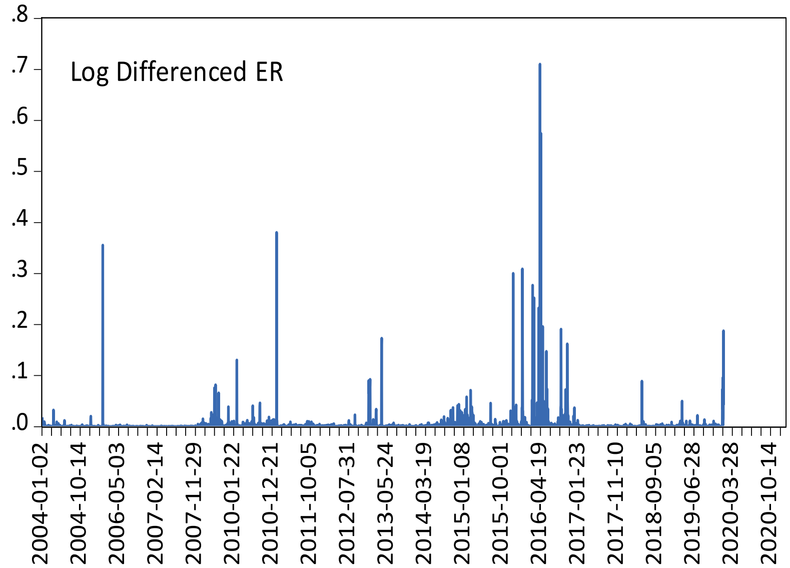

Figure 3. Log Exchange Rate Squared (SRD/USD)

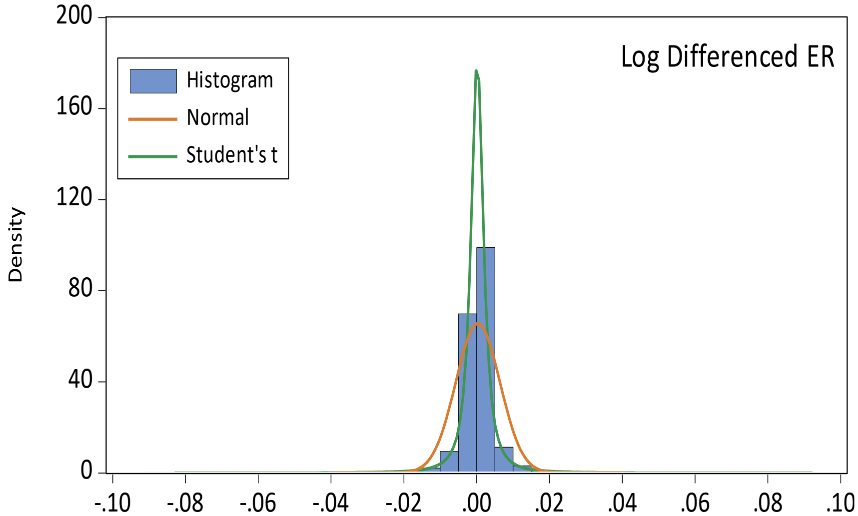

Figure 4. Statistical Distribution of the Exchange Rate

Figure 3 presents the distribution of the exchange rate data. The student's *t*-distribution is more peaked than a normal distribution. There is a significant difference between the maximum and minimum values and between the standard deviation and mean, which indicates high volatility. The kurtosis value, which is very large compared to the standardized value of 3.0, suggests the presence of a fat tail on the right side with respect to the mean and hence, the non-normality of the series.

Calibrated GARCH models

Following the GARCH procedure, we specify three main parts: the mean equation, the variance equation and the distribution error (table 1-3). First we calibrate GARCH(1,1)[9] and GARCH-M (1,1) models with Normal Gaussian distributions, Student's *t*-distributions, and GED. The GARCH(1,1) calibrated with the Gaussian distribution indicates that the mean and variance equations do not adequately capture the conditional volatility[10] (i.e. ARCH effects are detected in the model). When the model is calibrated with the student's *t*-distribution and GED, the mean equation is not well specified, but the variance equation was significant at the 10% and 5% level, respectively (still indicating that ARCH terms are presents). The normality test shows evidence of kurtosis and the Jarque-Bera test rejects the null hypothesis of normality. We then calibrate GARCH(2,2) and GARCH-M(2,2) models. The error terms again follow the Normal Gaussian distribution, Student's *t*-distributions, and GED. The models provided mixed results. A look at the diagnostic indicators reveals that the model still contains ARCH effects and has serial correlation problems. The existence of volatility clustering in the SRD/USD exchange rate is thus evident, see figure 1 and table 6 and 7 in Appendix I. We therefore proceed with calibrating higher order GARCH(p,q) models.

The third model we calibrate is a first order Threshold GARCH(1,1)(TGARCH), to test for asymmetric effects in the model.[11] We find that the model computed with the student's *t*-distribution delivered the best results with a positive R-squared value. The leverage coefficient value, -0.8149, is significant at the 10% level. The model fitted with the Normal Gaussian distribution also delivers adequate results. The coefficient value, -0.9170, is significant at the 5% level, but has a lower R-squared value.

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[9] We use EViews legacy with the Marquardt legacy method. We suspect that errors are not (conditionally) normally distributed, therefore we use the Huber-White covariance method to control for variances. We use, by default, the smoothing parameter 0.7 to compute the initial conditional variances for the models (if we use 1, the initial value is set to the unconditional variance (no backcasting). Remaining ARCH terms in the variance equation are detected by plotting correlogram squared residuals and performing an ARCH LM test. If the variance equation behaved well, all Q-statistics up to a maximum lag should be non-significant and no ARCH terms are left in the standardized residuals. The null hypothesis is that there are no ARCH terms in the standardized residuals.

[10] How do we select a GARCH model? We use three indicators to select the best models: the maximum value of the likelihood function, the Akaike Information Criterion (AIC) or the Schwartz Bayesian Criterion (SBC). We also check for the behavior of the model residuals.

[11] If the threshold coefficient is $\varepsilon_{t-k} > 0$, then it indicates that "bad" news (negative shocks) increase volatility more than "good" news. If $\varepsilon_{t-k} < 0$ then the opposite is true. This relationship indicates "leverage effects."

These results show that asymmetric effects in the variance equation are large and significant, which means previous models have ignored them. The coefficient is negative, an indication that "good" news drives volatility in the exchange rate more that "bad" news. We also calibrated a TGARCH(2,2)), but the mean equation coefficient was not improved. We also modelled an EGARCH-M(1,1) to test for leverage effects. Nevertheless, the mean equation indicated that there are still ARCH residuals present. The sign of the leverage effect is the opposite compared to the TARCH[12] (Dutta, 2014). Unlike the GARCH model, the EGARCH model places no restrictions on the estimated parameters to ensure non-negativity of the conditional variance. The EGARCH-M calibrated with the Gaussian distribution provides the best-fitted model. The leverage coefficient 2.374 is significant at the 1% level. The coefficient is larger than zero, indicating that positive shocks to the exogenous variable drive volatility more than negative shocks.

Now that we have established leverage effects, we test for persistent volatility (unit root) which makes volatility shocks permanent. For this purpose, we utilize the IGARCH (1,1) model. The results show that the IGARCH terms computed with the Gaussian error distribution provide better results. The ARCH term (-0.004) and GARCH term (1.004) are close to unity and significant at the 1% level. The IGARCH constrains the conditional variance to act like a unit root process. This implies that shocks to the conditional will be highly persistent. Now that we know that higher order GARCH(1,1) models indicate leverage effects and display excess kurtosis (fat tails) and persistent volatility, we run other higher order models to possibly improve the modelling of standard errors and volatility clustering.

We calibrate PARCH(1,1) and CGARCH(1,1) models. The results show that the PARCH(1,1) model calibrated with the Gaussian error distribution and GED provide useful results at the 1% significant level. The leverage and power coefficients are ε_{t-k} (0.9991) and $\delta = 0.3382$. The leverage and power coefficients with the GED are 0.9322 and 2.0919, respectively. The log likelihood parameter is smaller with the normal error distribution, which is better than with GED distribution (Normal 1247.336 vs. GED 1611.755). The last model calibration is CGARCH-M.

[12] If the leverage coefficient < 0, then it indicates that negative shocks drive volatility more than positive shocks.

Since we tested positive for persistent volatility clustering, it indicates that there may be a trend component and transitory component. The results show that the long-run component in the CGARCH-M, calibrated with the GED, was significant at 1% level. The long run coefficient was $\alpha(\varepsilon_{t-1}^2 - \delta_{t-1}^2)$ = 0.5382 and the transitory coefficient was $\beta(\sigma_{t-1}^2 - \delta_{t-1}^2)$ = 0.1529. Since earlier models indicate asymmetry, leverage effect, and volatility clustering, we combine the TGARCH and CGARCH-M to improve the standard errors. The results indicate that the model is well calibrated with all the three error distributions at the 1% significant level.

Gaussian distribution: $\varepsilon_{t-k} = 0.0755$; $\alpha(\varepsilon_{t-1}^2 - \delta_{t-1}^2)$ = 0.7116 and $\beta(\sigma_{t-1}^2 - \delta_{t-1}^2)$ = 0.0254
Student's *t*-distribution: $\varepsilon_{t-k} = 0.3029$; $\alpha(\varepsilon_{t-1}^2 - \delta_{t-1}^2)$ = 0.8985 and $\beta(\sigma_{t-1}^2 - \delta_{t-1}^2)$ = 0.0110
GED distribution: $\varepsilon_{t-k} = 0.3080$; $\alpha(\varepsilon_{t-1}^2 - \delta_{t-1}^2)$ = 0.9868 and $\beta(\sigma_{t-1}^2 - \delta_{t-1}^2)$ = 0.0253

However, the best model is the one calibrated with the GED, because the value (0.9868) denotes the speed at which the permanent component converges to its long-run value, which is, by convention, equal to one. Secondly, it denotes that the mean reversion occurs very slowly (0.0253). Notable is that, in this model combination, the leverage effect of the TARCH model changed sign (a leverage coefficient > 0, indicates that negative shocks drives volatility more than positive shocks).

Table 1. GARCH models calibrated with Normal Gaussian conditional errors

Models	Mean equation	Variance equation								Information Criterion		
	C	ARCH(1,1)	GARCH(1,1)	ARCH (2,2)	GARCH(2,2)	Leverage effect	Power parameter	Long-run component	Transitory component	AIC	BIC	Log likelihood
GARCH(1,1)	0.0160	0.0067	0.5287							-2.5202	-2.4479	396.6296
	(0.4151)	*(0.6941)*	*(0.1814)*									
GARCH(2,2)	0.0140	0.1165*	0.4404	-0.0616	-0.0085					-2.5962	-2.4997	410.4058
	(0.4222)	*(0.0034)*	*(0.1383)*	*(0.1321)*	*(0.9531)*							
GARCH-M(2,2)	*-0.0562*	*0.1094**	*0.3360*	*-0.0473*	*-0.0310*					-2.6660	-2.5575	422.2305
	(0.3975)	*(0.0065)*	*(0.1952)*	*(0.1489)*	*(0.6256)*							
TGARCH(1,1)	0.0205	0.1240	0.2599			-0.9170**				-2.5899	-2.5055	408.4332
	(0.0332)	*(0.0036)*	*(0.0001)*			*(0.0269)*						
EGARCH-M(1,1	0.000	-1.8433	0.1568			2.3737*				-3.2618	-3.1654	513.5778
	(0.3862)	*(0.0000)*	*(0.0000)*			*(0.0000)*						
IGARCH (1,1)	0.0044	-0.0040	1.0040							-2.9495	-2.9013	461.1697
	(0.1203)	*(0.0000)*	*(0.0001)*									
APARCH-M(1,1	-0.0073	-0.3508	1.1364			0.9981*	0.3382*			-3.3630	-3.255	530.2691
	(0.0001)	*(0.0000)*	*(0.0000)*			*(0.0000)*	*(0.0000)*					
CGARCH(1,1)	-0.0200	0.04001	0.1690					0.2326	0.0434	-2.7490	-2.6405	435.0949
	0.2511	*0.9486*	*0.5091*					*(0.3425)*	*(0.9443)*			
CGARCH-TGARCH(1,1)	-0.0156	(0.0239)**	(0.7741)*			0.0755*		0.7116*	0.0254*	-2.6954	-2.5749	427.7881
	(0.3619)	*(0.0133)*	*(0.0000)*			*(0.0000)*		*-0.0086*	*(0.0000)*			

Note: Standard errors are reported in parentheses. The p-values are presented in brackets. The sign (*), (**) and (***) represents the significance at the 1%, 5%, and 10% level.

Table 2. GARCH models with conditional Student's errors *t*-distribution

Models	Mean equation	Variance equation								Information Criterion		
	C	ARCH(1,1)	GARCH(1,1)	ARCH (2,2)	GARCH(2,2)	Leverage effect	Power parameter	Long-run component	Transitory component	AIC	BIC	Log likelihood
GARCH(1,1)	0.0100	0.0625	0.5273***							-2.7984	-2.7140	440.7549
	(0.5965)	*(0.1288)*	*(0.0922)*									
GARCH(2,2)	0.0101	0.0887**	0.3781*	-0.0407*	-0.046532					-3.0834	-2.975	486.9329
	(0.4728)	*(0.0216)*	*(0.0197)*	*(0.0000)*	*(0.5785)*							
GARCH-M(2,2)	*N.A*	*N.A*	*N.A*	*N.A*	*N.A*							
TGARCH(1,1)	0.0144	0.0406	0.5328			-0.8148***				-2.8326	-2.7362	447.0595
	(0.3170)	*(0.2301)*	*(0.0636)*			*(0.0793)*						
EGARCH-M(1,1)	-0.0639	-0.0001	0.0452			0.0001				-8.1238	-8.015	1268.191
	(0.9825)	*(0.9948)*	*(0.9786)*			*0.9917*						
IGARCH (1,1)	-0.0001	-0.0042	1.0042							-6.4630	-6.4028	1006.7680
	(0.8416)	*(0.0000)*	*(0.0001)*									
APARCH-M(1,1)	-0.0254	0.0038	0.0038			-0.8068	1.6457*			-7.9830	-7.862	1247.366
	(0.1385)	*(0.9293)*	*(0.8149)*			*(0.9522)*	*(0.0000)*					
CGARCH(1,1)	-0.0135	0.0479	0.1871					0.3303	0.0603	-3.6163	-3.4957	570.5218
	(0.2555)	*(0.9694)*	*(0.7748)*					*(0.4137)*	*(0.9615)*			
CGARCH-TGARCH(1,1)	-0.0170	0.0127**	(0.8701)*			0.3029*		0.8985*	0.0110*	-3.6163	-3.4957	570.5218
	(0.0019)	*(0.0431)*	*(0.000)*			*(0.0018)*		*(0.0000)*	*(0.0000)*			

Note: Standard errors are reported in parentheses. The p-values are presented in brackets. The sign (*), (**) and (***) represents the significance at the 1%, 5%, and 10% level.

Table 3. GARCH models calibrated with Generalized Error Distribution

Models	Mean equation			Variance equation						Information Criterion		
	C	ARCH(1,1)	GARCH(1,1)	ARCH (2,2)	GARCH(2,2)	Leverage effect	Power parameter	Long-run component	Transitory component	AIC	BIC	Log likelihood
GARCH(1,1)	0.0000	1.4014	0.3949**							-15.0474	-14.9630	2339.3490
	(0.8723)	*(0.3996)*	*(0.0307)*									
GARCH(2,2)	0.0090	0.1096*	0.436*	-0.0164	-0.007717					-2.6417	-2.7069	435.2837
	(0.6143)	*(0.0080)*	*(0.0812)*	*(0.7026)*	*(0.9805)*							
GARCH-M(2,2)	*0.0001*	*0.6515**	*0.6498**	*-0.4234**	*0.0000*					-13.9530	-13.832	2172.79
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.1494)*							
TGARCH(1,1)	0.0019	0.0091	0.5389			-0.5762				-3.0167	-2.9202	475.5832
	(0.9066)	*(0.6335)*	*(0.0000)*			*(0.5362)*						
EGARCH-M(1,1	-0.0253	0.0604	0.0449			0.07964*				-11.2552	-11.147	1753.555
	(0.0000)	*(0.0000)*	*(0.0000)*			*(0.0000)*						
IGARCH (1,1)	0.0000	-0.0048	1.0048							-11.3364	-11.2761	1762.1370
	(0.0000)	*(0.0000)*	*(0.0001)*									
APARCH-M(1,1	-0.1369	0.0654	0.4708			0.9322*	2.0919*			-10.3339	-10.213	1611.755
	(0.0000)	*(0.0000)*	*(0.0000)*			*(0.0000)*	*(0.0000)*					
CGARCH(1,1)	-0.000134	8.16E-05	-0.001039					0.5383*	0.1529*	-15.2720	-15.1515	2377.163
	0	0.3512	0					*(0.0000)*	*(0.0000)*			
CGARCH-TGARCH(1,1)	-0.0011	-0.0015	0.6469			0.3080*		0.9868*	0.0253*	-4.9573	-4.8247	779.3759
	0.3445	*(0.0000)*	*(0.0000)*			*(0.0000)*		*(0.0000)*	*(0.0000)*			

Note: Standard errors are reported in parentheses. The p-values are presented in brackets. The sign (*), (**) and (***) represents the significance at the 1%, 5%, and10% level.

Table 4 provides the criteria for the selection process out of 18 estimated models (6 higher order models multiplied by the three standardized distribution errors).

Table 4. Comparison of model accuracy

Models	Normal Distribution			Student's *t*- distribution			Generalized Error Distribution		
	AIC	SBC	Log likelihood	AIC	SBC	Log likelihood	AIC	SBC	Log likelihood
TGARCH	-2.5055	-2.5899	408.4332	-2.8326	-2.7362	447.0595	-3.0167	-2.9202	475.5832
EGARCH-M	-3.1654	-3.2618	513.5778	-8.1238	-8.0153	1268.1910	-11.2552	-11.1467	1753.5550
IGARCH	-2.9013	-2.9495	461.1697	-6.4630	-6.4028	1006.7680	-11.3364	-11.2761	1762.1370
APARCH-M	-3.2545	-3.3630	530.2691	-7.9830	-7.8625	1247.3660	-10.3339	-10.2134	1611.7550
CGARCH	-2.6405	-2.7490	435.0949	-3.6163	-3.4957	570.5218	-7.6761	-7.5677	1198.8020
CGARCH-TGARCH	-2.5749	-2.6954	427.7881	-4.1724	-4.0398	657.7260	-18.2205	-18.2929	2852.8620

Forecast accuracy

To analyze the accuracy of a conditional ER volatility forecast, we create an in-sample forecast using the period 2012m1-2019m11.[13] We compare the forecasting performance of the models with three indicators under Gaussian distribution, Student's *t*-distribution, and GED. From all the models calibrated with the distribution error, we select only one best fitted model to forecast. The results show that, for the Gaussian distribution, the best performing model is the combined CGARCH-M(1,1) and TGARCH(1,1). For the Student's *t*-distribution and GED, it is the TGARCH(1,1).

Table 5. Comparison of in-sample model forecasts

Models	Normal Distribution			Student's *t*- distribution			GED		
	RMSE	MAE	TI	RMSE	MAE	TI	RMSE	MAE	TI
TGARCH	0.0405	0.0240	0.6951	**0.0393**	**0.0202**	**0.7355**	**0.0395**	**0.0122**	**0.6573**
EGARCH-M	0.0399	0.0193	0.7641	0.3976	0.0116	0.9998	0.0396	0.0117	0.9812
IGARCH	0.0390	0.0136	0.8834	0.0396	0.1157	0.9709	0.0398	0.0116	0.9984
APARCH-M	0.0589	0.0491	0.6621	0.0398	0.0116	0.9993	0.0454	0.0360	0.6291
CGARCH	0.0392	0.0192	0.7522	0.0391	0.0145	0.8584	0.0398	0.0116	0.9993
CGARCH-TGARCH	**0.0392**	**0.0225**	**0.6812**	0.0424	0.0173	0.8791	0.0396	0.0133	0.8915

[13] This forecast sample was selected because, in this period, oil price and the exchange rate gradually came under pressure (see appendix I).

Conclusions

We estimate higher order GARCH(1,1) models to model conditional variances of the nominal SRD/USD exchange rate for the period 1994m1 to 2019m11. We use oil prices as the variance regressor and calibrate the models with the Gaussian error distribution, the Student's *t*-distribution, and the Generalized Error Distribution. Consequently, we perform in-sample forecasts for the period 2012m1-2019m11. For the model selection, and for measuring the accuracy of the forecast, we used the AIC, SBC, ML, RMSE, MAE and TI statistics. The best performing models are TGARCH(1,1) calibrated with the Student's *t*-distribution and GED and the model combination of CGARCH-M(1,1) and TGARCH(1,1) calibrated with the Normal Gaussian error distribution. These models indicate that when modelling conditional exchange rate variances, one should always account for leverage effects, persistent volatility, clustering of volatility, mean-reverting, excess kurtosis and trend and transitory components.

Discussion

Since we only have access to 311 monthly observations, we could not specify well-behaved mean equations with accepted p-values. With more observations available, we could improve the mean equations and simply model and forecast conditional variances with simple GARCH (1,1) and GARCH-M(1,1)(2,2) models. Because of this limitation, we calibrated higher order GARCH models to specify well-behaved variance equations and obtained useful results.

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Appendix I

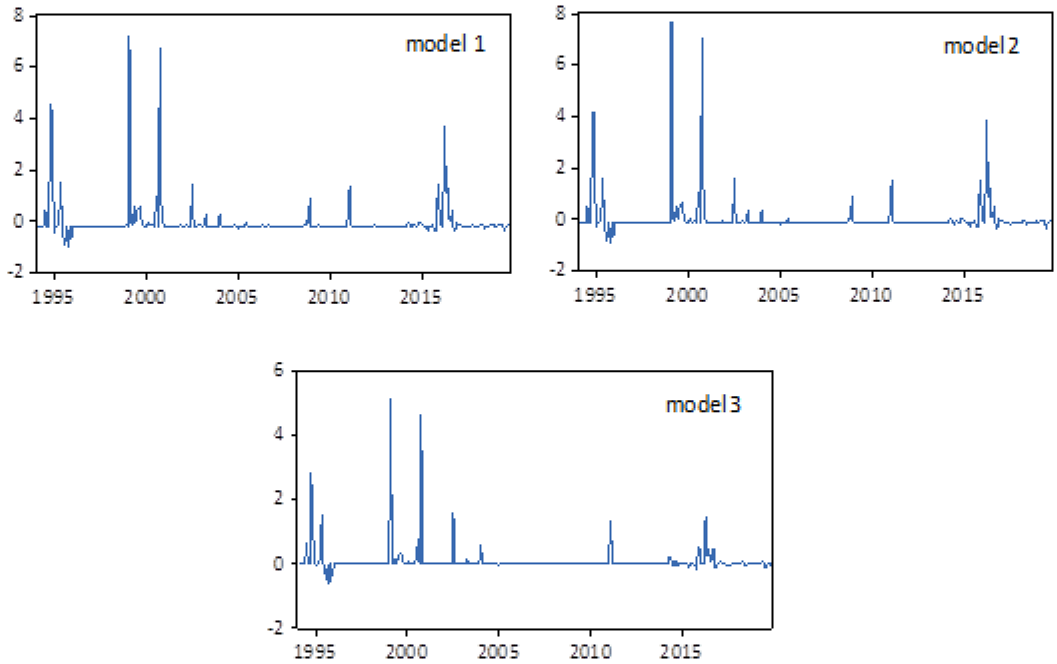

Figure 5. Volatility clustering of the nominal exchange rate of the SRD/USD.

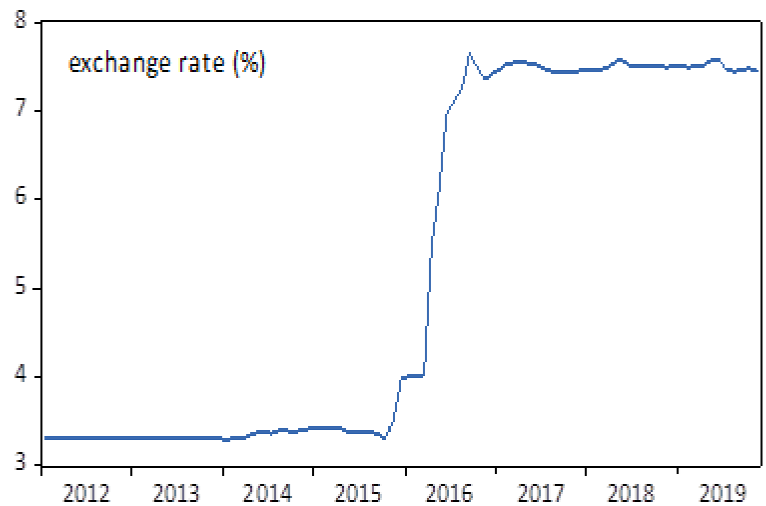

Figure 6. Evolution of the nominal exchange rate (SRD/USD). The pass-through effects of exchange rate to domestic economic activity is significant (see Bernhard Fritz-Krockow, 2009)

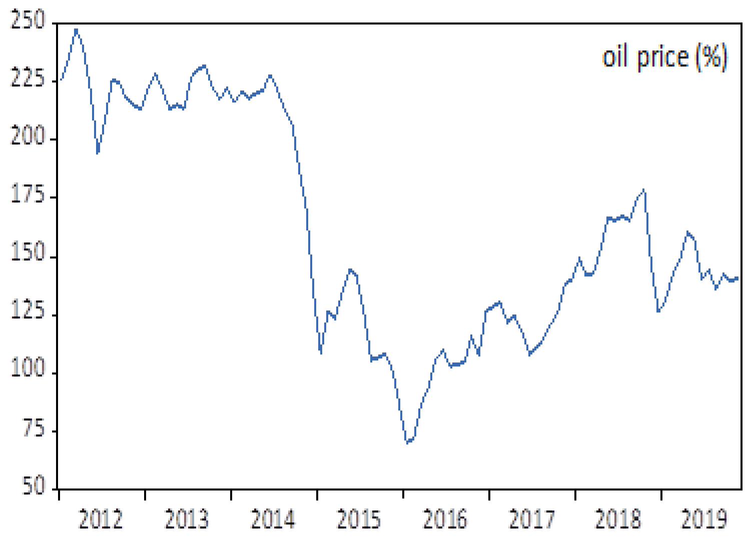

Figure 7. Volatility of the international WTI oil price

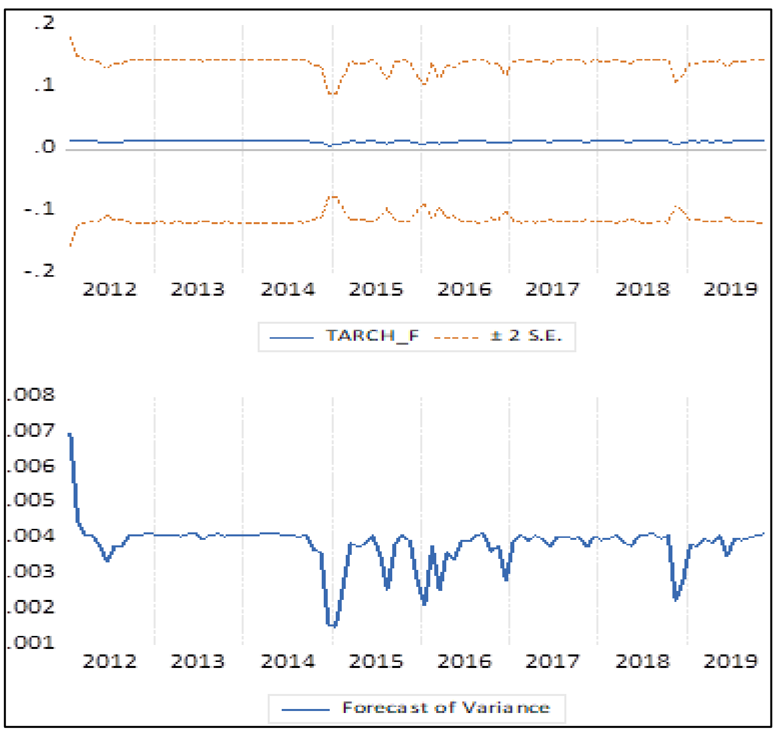

Figure 8. In-sample forecast with TGARCH(1,1) model (Student's t-distribution)

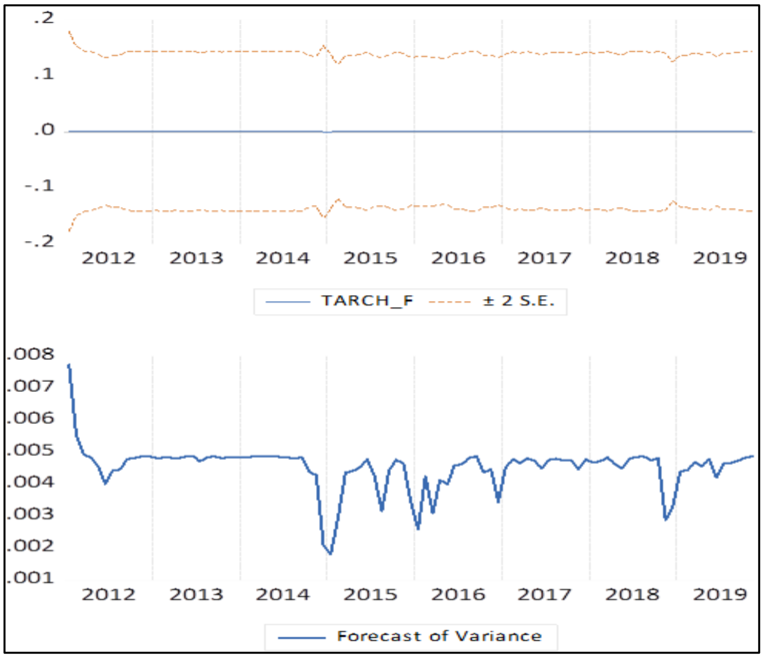

Figure 9. In-sample forecast with TGARCH(1,1) model (GED)

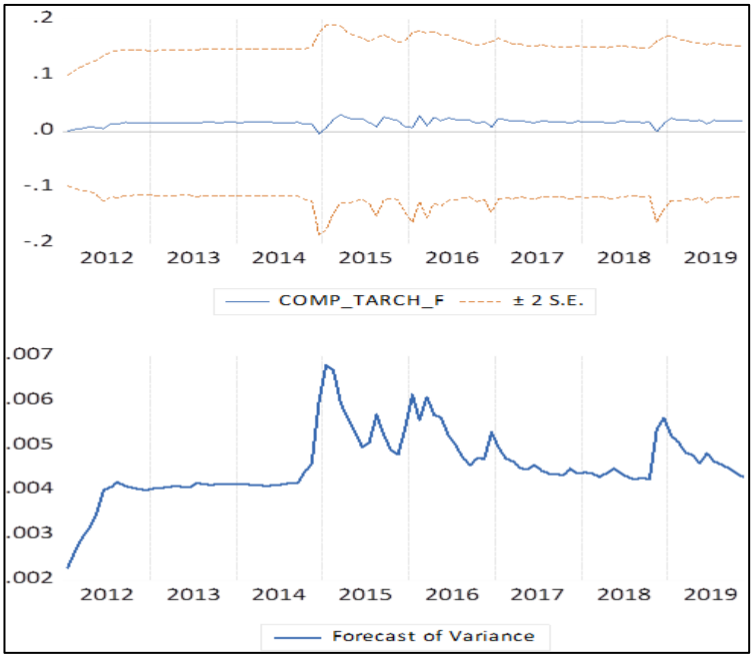

Figure 10. In-sample forecast with combined Component and TGARCH(1,1) model (Gaussian distribution).

Table 6: Test for serial correlation in the mean equation

	Auto Correlation	Partial Auto Correlation	Q-Statistics	Prob.
1	0.173	0.173	9.3931	0.002
2	0.074	0.045	11.094	0.004
3	0.039	0.019	11.562	0.009
4	0.032	0.020	11.891	0.018
5	0.053	0.043	12.783	0.025
6	0.058	0.040	13.840	0.031
7	0.017	-0.005	13.935	0.052
8	-0.038	-0.049	14.392	0.072
9	-0.047	-0.040	15.115	0.088
10	-0.036	-0.023	15.542	0.114
11	-0.051	-0.041	16.394	0.127
12	-0.031	-0.013	16.707	0.161
13	-0.011	0.006	16.750	0.211
14	-0.008	0.006	16.770	0.269
15	-0.003	0.008	16.773	0.333
16	-0.021	-0.015	16.914	0.391
17	0.029	0.039	17.188	0.442
18	0.028	0.020	17.452	0.492
19	-0.027	-0.044	17.693	0.543
20	0.285	0.301	44.854	0.001
21	0.052	-0.051	45.742	0.001
22	-0.028	-0.070	46.004	0.002
23	-0.015	-0.015	46.080	0.003
24	-0.020	-0.027	46.213	0.004
25	-0.027	-0.042	46.456	0.006
26	-0.032	-0.047	46.796	0.007
27	-0.029	-0.018	47.083	0.010
28	-0.029	0.016	47.373	0.013
29	-0.027	0.008	47.618	0.016
30	-0.016	0.004	47.702	0.021
31	-0.033	-0.002	48.079	0.026
32	-0.030	-0.011	48.395	0.032
33	-0.025	-0.019	48.614	0.039
34	-0.025	-0.020	48.831	0.048
35	-0.023	-0.025	49.025	0.058
36	-0.026	-0.004	49.257	0.069
37	-0.030	-0.046	49.573	0.081
38	-0.049	-0.062	50.443	0.085
39	-0.015	0.054	50.518	0.102
40	-0.066	-0.173	52.088	0.095

Table 7. Test for ARCH effects in the variance equation

	Auto Correlation	Partial Auto Correlation	Q-Statistics	Prob.
1	0.030	0.030	0.2870	0.592
2	0.003	0.002	0.2907	0.865
3	-0.007	-0.008	0.3081	0.959
4	-0.010	-0.009	0.3381	0.987
5	-0.008	-0.008	0.3610	0.996
6	0.001	0.002	0.3614	0.999
7	-0.007	-0.007	0.3774	1.000
8	-0.014	-0.014	0.4428	1.000
9	-0.013	-0.012	0.4952	1.000
10	-0.012	-0.011	0.5420	1.000
11	-0.010	-0.010	0.5763	1.000
12	-0.012	-0.011	0.6193	1.000
13	-0.007	-0.007	0.6374	1.000
14	-0.009	-0.010	0.6666	1.000
15	-0.011	-0.011	0.7041	1.000
16	-0.013	-0.013	0.7586	1.000
17	-0.006	-0.006	0.7704	1.000
18	-0.001	-0.002	0.7710	1.000
19	-0.013	-0.014	0.8281	1.000
20	0.421	0.421	59.920	0.000
21	0.010	-0.022	59.951	0.000
22	-0.013	-0.020	60.009	0.000
23	-0.013	-0.008	60.063	0.000
24	-0.013	-0.009	60.121	0.000
25	-0.013	-0.009	60.181	0.000
26	-0.013	-0.020	60.242	0.000
27	-0.013	-0.010	60.304	0.000
28	-0.013	-0.004	60.366	0.000
29	-0.014	-0.006	60.429	0.001
30	-0.012	-0.006	60.481	0.001
31	-0.014	-0.010	60.546	0.001
32	-0.014	-0.008	60.610	0.002
33	-0.014	-0.011	60.676	0.002
34	-0.014	-0.007	60.740	0.003
35	-0.014	-0.008	60.806	0.004
36	-0.014	-0.006	60.872	0.006
37	-0.014	-0.013	60.941	0.008
38	-0.011	-0.012	60.983	0.010
39	-0.012	0.005	61.036	0.014
40	-0.008	-0.229	61.062	0.018