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Assessing the Forecasting Performance of GARCH Models in the Presence of Instabilities

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Abstract Proper modeling and anticipation of business volatility play an important role in risk management, derivatives allocations, and the price of assets in a finance research field. Hence, it means the requirement for forecasting models that deliver accurate forecasts during those periods. An accurate forecasting model is critical for interpreting financial data, and confirming the time series is stationary is a vital step in model development. Moreover, one must select a model that does well in a particular asset class. There is no single best model across all asset classes and periods. As a result, identifying a model that performs well in specific asset classes is critical. Several forecasting models are available to decision-makers, and no single model emerges as the best all-around. This is due to instability in predicting performance, which varies by state and is based on time-varying economic factors. As a result, this study compares the forecasting abilities of some GARCH models for exchange rate data on the South African market by using traditional and fluctuation tests within normal students, and general error distribution assumptions. Forecast accuracy was assessed using four model accuracy measures: root mean square error, mean absolute error, mean absolute percentage error, and the Theil inequality coefficient. The Giacomini and Rossi (2010) fluctuations test and the Diebold and Mariano test were used to evaluate relative predicting skills in the face of instabilities. In contrast, the Rossi-Sekhposyan (2016) test was utilized to determine if absolute predicting performance is robust to instabilities. It is revealed that symmetric GARCH models do not overperform those models with asymmetry under several assessment indicators and error distributions. Giacomini and Rossi's (2010) test confirms the efficiency of all models undertaking the t-distribution approach. However, the Sekhpoysan (2016) test suggested that despite all models generating good forecasts, an individual model might be making weak predictions compared to the others. The practical implication is that all models can make accurate predictions. It may perform poorly solely when compared to other models.

Keywords Forecasting Abilities, Traditional Tests, Fluctuation Tests, Symmetric GARCH Models, Asymmetric GARCH Models, Exchange Rate Data, South Africa

1. Introduction

Accurate modeling and forecasting of market volatility are crucial for risk management, derivative allocation, and asset pricing in finance research [1]. A reliable forecasting model is crucial for analyzing financial data, and ensuring the time series is stationary is a key step in developing a model. A stationary time series has the property that its variance, mean, and autocorrelation structure remain constant over time [2]. The use of non-stationary time series data in financial models results in unreliable and spurious outcomes, causing poor understanding and forecasting [3].

Fluctuation tests were proposed to circumvent the consequences associated with stationarity assumptions when making inferences concerning predictive ability. Examples are Giacomini and Rossi [4] and Rossi and Sekhposyan [5] test. In contrast to Giacomini and Rossi [4] who measure models' relative predictive performance, Rossi and Sekhposyan [5] consider single models' absolute predictability ability and forecast optimality.

Uncertainty in the modelling of the underlying asset will appear as a risk in derivative pricing and hedging. There is typically a way to price and hedge financial derivatives (currencies in this case) with high accuracy if one has a good model of the underlying asset. Using an incorrect pricing and hedging model may lead to unexpected and undesirable financial outcomes [6].

No single model is optimal across all asset classes and periods [7]. Therefore, finding a model that performs well in specific asset classes is crucial. Odendahl, et al. [8] also stressed that "decision-makers face numerous forecasting models, with no single model emerging as the best overall. This is due to instabilities in forecasting performance, which depends on the sample and is state-dependent due to time-varying economic mechanisms." As a result, this study compares asymmetric and asymmetric GARCH models using the exchange rate as a financial asset, aiming to find a model that performs better in this asset class. Furthermore, it will also aim to determine whether the preferred model performs better in the short or long horizon.

The literature on models addressing instabilities is limited, especially in South Africa. Previous studies have used traditional techniques to compare forecasting models, but this paper will employ models that are robust to instabilities, which is a crucial aspect of financial risk management. Given this, the present paper makes a comparison of the forecasting performance of symmetric and asymmetric GARCH models in the presence of instabilities using non-stationary data under different distribution errors.

2. Materials and Methods

This section outlines the research methodology, discussing both theoretical and empirical models, data description, and out-of-sample evaluation of volatility forecasts in subsections 2.1, 2.2, 2.3, and 2.4 respectively.

2.1. Symmetric and Asymmetric Models

Symmetric GARCH models differ from asymmetric ones in that they do not incorporate asymmetry found in the returns financial data. This implies that bad news surprises increase conditioned variance more than equivalent good news.

- **Generalized autoregressive conditional heteroscedasticity (GARCH)**

GARCH was first presented by Bollerslev [9] and is a generalization of the earlier ARCH model [10].

The GARCH (1, 1) model is stated as:

$$h_{t+1}^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 \tag{1}$$

In this case, all the parameters must be positive, while the sum of $(\alpha + \beta)$, measures the persistence of shocks to volatility. The GARCH (1, 1) model generates one-step-ahead forecasts of volatility as a weighted average of the constant long-run or average variance, ω, the previous forecast variance, h_t^2 and previous volatility reflecting squared 'news' about the return, ε_t^2. As volatility forecasts are increased following a large return of either sign, the GARCH specification captures the well-known volatility clustering effect.

- **Exponential General Autoregressive conditional heteroscedasticity (EGARCH)**

A modification of the GARCH model introduced by Nelson [11] is the exponential generalized autoregressive conditional heteroskedastic time series model and is also identified using the abbreviation, EGARCH. The model is taken from ARCH family models that have been propounded for handling the volatility in time series data [12]. These models make the conditional variance as a function of time (t) [11, 13]. Later, Nelson [11] suggested that the EGARCH model captures volatility asymmetries exponentially, allowing skewness and asymmetrical ARCH processes. Conditional variance is an asymmetric function of the lagged disturbances, ε_{t-i} .

The model is stated as follows:

$$\varepsilon_t = \sigma_t Z_t;\ ln\sigma^2 = \omega + \alpha_i \varepsilon_{t-i}{}^2 + \sum_{j=1}^{q} \gamma_j \ln \sigma_{t-j}^2 \tag{2}$$

On its part, when $\gamma < 0$ captures the larger impact on the market by negative shocks, than positive shocks of equivalent magnitude, and a significant α captures the volatility clusters effect. The last point regards using a logarithm form. Because of this property of the log, if parameters are negative then the conditional variance will not become negative itself.

- **Threshold general autoregressive conditional heteroscedasticity (TGARCH) model**

The Threshold GARCH (TGARCH) model, presented by Glosten, et al. [14] and Zakoian [15] introduces a model that distinguishes between the impact of positive and negative news on conditional variance.

The TGARCH model of order q can be written as:

$$\sigma_t^2 = w \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{t=1}^{p} \alpha_i\, \varepsilon_{t-i} + \sum_{k=1}^{r} \gamma k\, \varepsilon_{t-k} \mathrm{I}_{t-k}) \tag{3}$$

In this model, good news, $\varepsilon_{t-i} > 0$, and bad news, $\varepsilon_{t-i} < 0$ have differential effects on the conditional variance. Here, α_i has an impact of good news while $\alpha_i + \gamma_i$ has an impact of bad news. If $\gamma_i > 0$, bad news has a greater impact of conditional variance, whereas if $\gamma_i \neq 0$, news impact is asymmetric.

- **Asymmetric power autoregressive conditional heteroscedasticity (APARCH) model**

Ding, Granger, and Engle [1] introduced the APARCH model, which estimates the power δ of the heteroscedasticity equation from data. This model captures asymmetry in return volatility, showing volatility increases more with positive returns. The power parameter on the standard deviation is estimated and not imposed:

$$h_t^{\delta}=\omega\ +\alpha_1(|\varepsilon_{t-1}|-\gamma\varepsilon_{t-1})\delta+\beta_1 h_t^{\delta} \quad (4)$$

Parameter δ in the equation denotes the exponent of conditional standard deviation, while parameter γ describes the asymmetry effect of good and bad news on conditional volatility. A positive value of γ means that negative shocks from the previous period have a higher impact on the current level of volatility, and otherwise [16].

An APARCH (p, q) model assumes that:

$$\sigma_t^{\delta}=\omega\ +\alpha_i(|\varepsilon_{t-1}|-\gamma\varepsilon_{t-1})\delta+\beta_j\sigma_t^{\delta} \quad (5)$$

A positive (resp. negative) value of γ_i's means that past negative (resp. positive) shocks have a deeper impact on current conditional volatility than past positive shocks ([17, 18].

- **Integrated general conditional heteroscedasticity (IGARCH) model**

Engle and Bollerslev [19] introduced the integrated GARCH (IGARCH) model, which incorporates exponential decay in the autocorrelation of conditional variances to account for volatility persistence. This model highlights the long-lasting impact of shocks in financial asset returns.

IGARCH models, which have a unit root in the AR polynomial of the GARCH representation, capture the effect of shocks on future volatility over an infinite horizon [20].

The integrated GARCH (IGARCH) is specified as:

$$\sigma_t^2=\omega+\sum_{i=1}^{P}\alpha_i\,{\varepsilon_{t-i}}^2+\sum_{j=1}^{q}\beta_j\quad\sigma_{t-j}^2 \quad (6)$$

The sum of coefficients is restricted to 1. The exogenous variable can be easily reflected in the various specifications of GARCH models just by the addition of α and β.

2.2. Specification of the Models

This section presents the empirical models that are employed in this study.

2.2.1. Empirical Models

The empirical models are stated as follows:

- **GARCH (1, 1) model**

A simple GARCH model can be stated as follows:

$$\text{R/US\$}_t=\omega+\alpha\varepsilon_{t-1}^2\ +\beta US\$_{t-1}\ +\varepsilon_t \quad (7)$$

Where the forecast variance of Rand/US$ daily exchange rate is represented by $\text{R/US\$}_t$.

- **Exponential GARCH (EGARCH) model**

EGARCH (1, 1) model can be written as:

$$ln\text{R/US\$}\ _t=\ \omega+\alpha_i{\varepsilon_{t-i}}^2+\sum_{j=1}^{q}\gamma_j\ln\text{R/US\$}_{t-j} \quad (8)$$

- **Threshold GARCH (TGARCH) model**

The TGARCH model of order q can be written as:

$$\text{R/US\$}\ _t=\ =\ w\sum_{t-1}^{q}\alpha_i\varepsilon_{t-i}^{\delta}+w\sum_{t-1}^{q}\alpha_{t-i}^{-}I(\varepsilon_{t-i}<0) \quad (9)$$

- **Asymmetric ARCH (APARCH) model**

The APARCH model can be stated as:

$$R/US\$_t=\omega\ +\alpha_1(|\varepsilon_{t-1}|-\gamma\varepsilon_{t-1})\delta+\beta_1 R/US\$_{t-1} \quad (10)$$

- **Integrated GARCH (IGARCH) model**

The IGARCH model is as follows:

$$R/US\$_t=\omega+\sum_{i=1}^{P}\alpha_i\,{\varepsilon_{t-i}}^2+\sum_{j=1}^{q}\beta_j\quad R/US\$_{t-j} \quad (11)$$

2.3. Description of the Type of Sample to be Used

The study uses a 5-day week Rand per US Dollar rate sourced from the Federal Reserve Economic Data (FRED) online, covering the period 2007/01/01 to 2018/12/31. Both the EViews and Stata software packages were employed.

2.4. Out-of- sample Forecasting

2.4.1. Evaluation Forecasting Criteria

Different models are used to assess forecast accuracy, but individual models may face misspecification bias. Combining forecasts across models can help robustify predictions against these biases and measurement errors. Combining individual model forecasts can enhance forecast accuracy and predictive ability [21, 22]. This study uses four model accuracy measures: Root Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and Theil Inequality coefficient to select the best model for out-of-sample forecast using EViews 11 software. The data sample will be divided into three periods: 2007-2018, 2007-2008, and 2008-2009.

3. Results

3.1. Results for Forecast Performance Evaluation of the Models

The results for the three sample periods (2007 to 2018, 2007 to 2008 and 2009 to 2018) are presented in Tables 1, 2 and 3 respectively.

- **2007-2018 sample period**

The sample period 2007 to 2018 combines both the period of crisis and normal (post-crisis) period. Table 1 results reveal that the IGARCH model is the best performer in terms of out-of-sample forecasting in 2 of the 4 criteria (RMSE and Theil's Inequality coefficient) under the 3 distribution errors (normal, student-t and general error distribution). The CGARCH model follows closely holding the second-best performance in 1 out of 4 criteria (MAE) under the 3 distribution errors. We can thus conclude that asymmetric models have the better out-of-sample fit relative to symmetric ones. This is depicted in Table 1 below.

Table 1. Evaluation of out-of-sample volatility forecasts (2007-2018)

Model	Distribution	RMSE	MAE	MAPE	Theil Inequality coefficient
PARCH	Normal	3.784345	2.788958	23.04458	0.211135
PARCH	Student-t	3.671928	2.703921	22.41857	0.202951
PARCH	Generalized Error	3.784345	2.788958	23.04458	0.211135
TARCH	Normal	10.44803	10.08103	100.0000	1.000000
TARCH	Student-t	3.663741	2.698245	22.38051	0.202390
TARCH	Generalized Error	3.524451	2.612557	21.89078	0.192401
EGARCH	Normal	3.686247	2.714032	22.48780	0.204015
EGARCH	Student-t	3.629838	2.675373	**22.23225**	0.199949
EGARCH	Generalized Error	3.682598	2.711430	22.46980	0.203757
IGARCH	Normal	**2.744837**	2.422447	25.19064	**0.133705**
IGARCH	Student-t	**2.744837**	2.422447	25.19064	**0.133705**
IGARCH	Generalized Error	**2.744837**	2.422447	25.19064	**0.133705**
CGARCH	Normal	2.747718	**2.412758**	24.77677	0.134683
CGARCH	Student-t	2.820988	**2.405598**	23.403812	0.141915
CGARCH	Generalized Error	2.753087	**2.408660**	24.52213	0.135513
GARCH (1,1)	Normal	3.665967	2.699781	**22.39075**	0.202551
GARCH (1,1)	Student-t	3.665967	2.699781	22.39075	0.202551
GARCH (1,1)	Generalized Error	3.515519	2.607668	**21.86835**	0.191764

Sample 2007-2008

From Table 2 below, the period 2007 to 2008 is the global financial crisis. Under the 2 error distributions (normal and general error), the IGARCH model holds the best performance in 2 out of 4 criteria (RMSE and Theil's U coefficient) respectively, and the CGARCH model, holding the best performance in 2 out of 4 criteria (MAE and MAPE) under normal distribution and 2 out of 4 criteria (RMSE and Theil's inequality coefficient) under student-t distribution. This suggests that asymmetric models outperform symmetric models during the crisis period.

Sample 2009-2018

Among three error distributions, Gaussian (normal), student-t, and general error, IGARCH demonstrated superior performance in three of the four criteria (RMSE, MAE, and Theil's U coefficient). Following closely is the APARCH model, excelling in MAPE under normal and student-t distributions, and in MAE under general error distribution. This leads to the conclusion that asymmetric models outperform symmetric models, even in post-crisis periods.

Table 2. Evaluation of out-of-sample volatility forecasts (2007-2008)

Model	Distribution	RMSE	MAE	MAPE	Theil Inequality coefficient
GARCH (1,1)	Normal	1.082091	0.655106	7.561632	0.072662
GARCH (1,1)	Student-t	1.082091	0.655106	7.561632	0.072662
GARCH (1,1)	Generalized Error	1.075951	**0.651899**	**7.531559**	0.072182
EGARCH	Normal	1.077125	0.652386	7.535525	0.072274
EGARCH	Student-t	1.077121	0.652384	7.535507	0.072273
EGARCH	Generalized Error	1.080030	0.653865	7.549215	0.072501
IGARCH	Normal	0.968216	0.693303	8.59484	0.062865
IGARCH	Student-t	1.108572	0.672737	7.747772	0.074724
IGARCH	Generalized Error	**0.973165**	0.660929	8.010454	**0.063946**
TARCH	Normal	1.080948	0.654399	7.554471	0.072572
TARCH	Student-t	1.080362	0.654057	7.551100	0.072527
TARCH	Generalized Error	1.080362	0.654057	7.551100	0.072527
PARCH	Normal	1.077086	0.652368	7.535370	0.072271
PARCH	Student-t	1.077084	**0.652367**	**7.535363**	0.192495
PARCH	Generalized Error	1.080888	0.654361	7.554091	0.072568
CGARCH	Normal	1.077066	0.652360	7.535304	0.072269
CGARCH	Student-t	**0.971378**	0.666134	8.121105	**0.063515**
CGARCH	Generalized Error	1.095337	0.663784	7.652106	0.073694

Table 3. Evaluation of out-of-sample volatility forecasts (2009-2018)

Model	Distribution	RMSE	MAE	MAPE	Theil Inequality coefficient
GARCH (1,1)	Normal	3.629846	2.838667	23.42160	0.190177
GARCH (1,1)	Student-t	3.629846	2.838667	23.42161	0.190177
GARCH (1,1) *	Generalized Error	2.758000	2.409495	23.57475	0.130909
EGARCH	Normal	3.533992	2.729504	22.31258	0.185042
EGARCH	Student-t	3.534000	2.729510	22.31263	0.185042
EGARCH	Generalized Error	3.022094	2.514999	**22.03074**	0.151329
IGARCH	Normal	**2.630252**	**2.401867**	24.27654	**0.122573**
IGARCH	Student-t	**2.630252**	**2.401867**	24.27654	**0.122573**
IGARCH	Generalized Error	**2.630252**	**2.401867**	24.27654	**0.122573**
TARCH	Normal	2.725294	2.409647	24.75462	0.126943
TARCH	Student-t	2.759593	2.410049	23.55591	0.131050
TARCH	Generalized Error	2.761630	2.410781	23.53286	0.131228
PARCH	Normal	3.366601	2.637627	**21.89361**	0.173919
PARCH	Student-t	3.447897	2.677108	**22.03026**	0.179304
PARCH	Generalized Error	2.703594	**2.401867**	22.83977	0.129774
CGARCH	Normal	2.726649	2.405209	24.48510	0.126943
CGARCH	Student-t	2.727503	2.403517	24.31863	0.127368
CGARCH	Generalized Error	2.726656	2.405099	24.47585	0.126964

3.2. Tests of Forecasting Performance Robust to Instabilities

3.2.1. Tests of Relative Forecasting Performance Robust to Instabilities

The comparison between the outcomes of the new and old methods (specifically, the Giacomini and Rossi [4] fluctuation test and the Diebold and Mariano [23] test) is presented in Table 4. These results reveal that when examining models accommodating instabilities, the error assumption based on the t-distribution outperforms other error distribution assumptions. This suggests that all models perform well when operating under the t-distribution assumption, especially when forecasters aim to use GARCH models for predicting series, notably exchange rates, while considering inherent instabilities. Conversely, in the realm of traditional tests, both t-distribution and general error distribution assumptions take precedence, with the t-distribution assumption leading the way.

Table 4. Relative comparison (distribution vs distribution)

		Accounting for instabilities: Giacomini and Rossi (2010) test				Traditional tests: Diebold & Mariano (2010) test				
Competing Models		t-statistic	Critical value	Conclusion on the hypothesis that 2 models have same forecast accuracy	dominant distribution	MSE criterion	MSE criterion	P-value	Conclusion on the hypothesis that 2 models have same forecast accuracy	dominant distribution
Model 1	Model 2					Model 1	Model 2			
$Garch_t$	$Garch_{normal}$	3.9213176	3.393	We reject H_0 and conclude Garcht is best	t dominates as it is better than normal and ged; followed by ged which is better than normal	0.1358	0.01364	0.0002	GARCHt dominates	t dominates as it is better than normal and ged
$Garch_t$	$Garch_{ged}$	3.7944076	3.393	We reject H_0		0.1358	0.01364	0.0005	GARCHt dominates	
$Garch_{ged}$	$Garch_{normal}$	2.5557673	3.393	We fail to reject H_0		0.01364	0.01364	0.8995	GARCHged equals to GARCHnor	
$IGarch_t$	$IGarch_{normal}$	4.0300879	3.393	We reject H_0	t dominates as it is better than normal and ged; followed by ged which is better than normal	0.01357	0.01362	0.0000	IGARCHt dominates	t dominates as it is better than normal and ged;,
$IGarch_t$	$IGarch_{ged}$	3.9307961	3.393	We reject H_0		0.01357	0.01361	0.0000	IGARCHt dominates	
$IGarch_{ged}$	$IGarch_{normal}$	3.5585911	3.393	We reject H_0		0.01361	0.01362	0.0020	IGARCHged dominates	
$TGarch_t$	$TGarch_{normal}$	3.9674876	3.393	We reject H_0	t dominates as it is better than normal and ged; followed by ged which is better than normal	0.01358	0.01365	0.0000	TGARCHt dominates	t dominates as it is better than normal and ged;
$TGarch_t$	$TGarch_{ged}$	3.8006337	3.393	We reject H_0		0.01358	0.01364	0.0003	TGARCHt dominates	
$TGarch_{ged}$	$TGarch_{normal}$	3.2511346	3.393	We fail to reject H_0		0.01364	0.01365	0.1205	TGARCHged equals to TGARCHnor	

Table 4. Continued

$EGarch_t$	$EGarch_{normal}$	3.8903286	3.393	We reject H0	t dominates as it is better than normal and ged; followed by ged which is better than normal	0.01358	0.01368	0.0008	EGARCHt dominates	t dominates as it is better than normal and ged;
$EGarch_t$	$EGarch_{ged}$	3.7139485	3.393	We reject H0		0.01358	0.01368	0.0016	EGARCHt dominates	
$EGarch_{ged}$	$EGarch_{normal}$	3.6064937	3.393	We reject H0		0.01368	0.01368	0.8725	EGARCHged quals to EGARCHnor	
$APARCH_t$	$APARCH_{normal}$	4.4628382	3.393	We reject H0	t dominates as it is better than normal and ged; followed by ged which is better than normal	0.01373	0.01383	0.0000	APARCHt dominates	t dominates as it is better than normal and ged;
$APARCH_t$	$APARCH_{ged}$	4.0508819	3.393	We reject H0		0.01373	0.01377	0.0065	APARCHt dominates	
$APARCH_{ged}$	$APARCH_{normal}$	4.3404236	3.393	We reject H0		0.01377	0.01383	0.0008	APARCHged dominates	

Table 5. Rossi – Sekhposyan's (2016) test statistics

Model	t-stat	Critical value	Conclusion
Garchnor	45.007565	69	Rejects the null hypothesis of forecast rationality
Garcht	42.049564	75	Rejects the null hypothesis of forecast rationality
Garchged	42.153557	81	Rejects the null hypothesis of forecast rationality
EGarchnor	41.328762	343	Rejects the null hypothesis of forecast rationality
EGarcht	37.562038	349	Rejects the null hypothesis of forecast rationality
EGarchged	38.51445	355	Rejects the null hypothesis of forecast rationality
IGarchnor	47.630093	164	Rejects the null hypothesis of forecast rationality
IGarcht	42.531448	170	Rejects the null hypothesis of forecast rationality
IGarchged	46.108101	176	Rejects the null hypothesis of forecast rationality
TGarchnor	44.215855	254	Rejects the null hypothesis of forecast rationality
TGarcht	43.603016	260	Rejects the null hypothesis of forecast rationality
TGarchged	42.600109	266	Rejects the null hypothesis of forecast rationality
AParchnor	69.572197	432	Rejects the null hypothesis of forecast rationality
AParcht	64.624062	438	Rejects the null hypothesis of forecast rationality
AParchged	57.134777	444	Rejects the null hypothesis of forecast rationality

3.2.2. Tests of Absolute Forecasting Performance Robust to Instabilities

Classic tests for forecast rationality, like those by Mincer and Zarnowitz [24] and West and McCracken [25], rely on the assumption of stationarity, making them unsuitable when dealing with instabilities as noted by Rossi, et al. [26]. In contrast, the fluctuation rationality test, as proposed by de Prince, et al. [27], aligns with the concept of instability, resulting in a reduced likelihood of rejecting the null hypothesis of forecast rationality compared to traditional tests.

From Table 5 above, the forecast rationality is not supported in each model, as the Rossi-Sekhposyan test statistics indicate rejection of the null assumption, implying that forecast errors are predictable by all the models under review. Consequently, each of these models does well, meaning that they can make a good prediction. It is only if one model has to be chosen from several pools that matter. This explains the outcomes of the relative comparison which reveal that certain models are worse off.

4. Discussion

The results from the three sample periods exhibit that different asymmetric models outperform symmetric ones under different evaluation criteria with different error distributions. Hence, asymmetric GARCH models can be said to have better forecasting performance with regard to out-of-sample forecast.

All other distribution assumptions are outperformed by t- distribution error assumption which gives an impression that the model is good with t- distribution error assumption. However, even with a traditional test, the t-distribution comes first.

The individual models results derived from the Rossi – Sekhposyan test statistics are such that each model works well. It is only when a model is compared with another one that it can be said to have poor performance.

5. Conclusions

Combining predictions from different models has an average improvement in accuracy compared to the individual models as shown by the outcome from all three sampled cases. Three out of four model's accuracy indexes (RMSE, MAE and Theil inequality coefficient) indicated the IGARCH model as the best performer. This conforms to Stenberg [10] who used MAPE and RMSE. Their results indicate, as a matter of fact, that the forecasting model used consistently produced highly accurate predictions and compared well to other models for each currency studied. Similarly, Preminger and Raphael [28] noted that forecast performance measures including MAE, MAPE, RMSE and Theil U statistic can be quite beneficial in terms of choosing the best model.

This coincides with what Shen, et al. [29] did using the MAPE and the RMSE. Their findings indicate that the applied method of prediction produces remarkably high levels of precision, which is superior for all currencies to compete models. This supports Timmermann [21], who demonstrated that combining several prediction models can give on average more accuracy than that of the individual models.

Based on the findings of this study, we therefore conclude that symmetric models can outperform asymmetric ones under t-distribution, which is inconsistent with previous literature that suggests that asymmetric models outdo symmetric ones in terms of forecasting under non-normal distributions due to their ability to capture asymmetric effect. We can therefore conclude that symmetric models should also be used in forecasting as they can make better forecast than asymmetric ones. The practical implication is that all models can produce accurate forecasts. Only when compared to another model (other models) does it exhibit poor performance.

As the results indicate that traditional tests can yield accurate predictions as well, we can thus suggest that future studies on similar topics should explore diverse error distributions and utilize both traditional and innovative techniques. These variations might yield different results from previous findings, which stated that traditional models falter in making accurate predictions during periods of macroeconomic weaknesses. Exploring more advanced GARCH models across short and long-term horizons could shed further light and potentially support the current findings.

Finally, there appears to be a lack of literature on studies that combine traditional models with robust new techniques designed to handle instabilities. This study aims to bridge that gap and contribute significantly to this area of research.

REFERENCES

[1] Ding, Zhuanxin, Clive WJ Granger, and Robert F. Engle. "A long memory property of stock market returns and a new model." *Journal of Empirical Finance,* vol. 1, no. 1, pp. 83-106, 1993. https://doi.org/10.1016/0927-5398(93)90006-D

[2] Jobo, Jongikhaya. *Exchange rate currency forecasting with Realized GARCH model*. University of Johannesburg (South Africa), 2022.

[3] Maleki, Negar, Alireza Nikoubin, Masoud Rabbani, and Yasser Zeinali. "Bitcoin price prediction based on other cryptocurrencies using machine learning and time series analysis." *Scientia Iranica,* 2020.

[4] Giacomini, Raffaella, and Barbara Rossi. "Forecast comparisons in unstable environments." *Journal of Applied Econometrics,* vol. 25, no. 4, pp. 595-620, 2010. https://doi.org/10.1002/jae.1177

[5] Rossi, Barbara, and Tatevik Sekhposyan. "Forecast rationality tests in the presence of instabilities, with applications to Federal Reserve and survey forecasts." *Journal of Applied Econometrics*, vol. 31, no. 3, pp. 507-532, 2016. https://doi.org/10.1002/jae.2440

[6] Gupta, Alok, Christoph Reisinger, and Alan Whitley. "Model uncertainty and its impact on derivative pricing." 2011.

[7] Basnet, Bikash. "The Predictive Power of Alternative Volatility Forecasting Models over Multiple Horizons." Master's thesis, Universitetet i Agder; University of Agder, 2016.

[8] Odendahl, Florens, Barbara Rossi, and Tatevik Sekhposyan. "Evaluating forecast performance with state dependence." *Journal of Econometrics,* vol. 237, no. 2, Part C, 2023. https://doi.org/10.1016/j.jeconom.2021.07.015

[9] Bollerslev, Tim. "Generalized autoregressive conditional heteroskedasticity." *Journal of Econometrics,* vol. 31, no. 3, pp. 307-327, 1986. https://doi.org/10.1016/0304-4076(86)90063-1

[10] Stenberg, Erik. "On the Autoregressive Conditional Heteroskedasticity Models." 2016.

[11] Nelson, Daniel B. "Conditional heteroskedasticity in asset returns: A new approach." *Econometrica,* vol. 59, no. 2, pp. 347-370, 1991. https://doi.org/10.2307/2938260

[12] Francq, Christian, and Jean-Michel Zakoïan. "Inconsistency of the MLE and inference based on weighted LS for LARCH models." *Journal of Econometrics,* vol. 159, no. 1, pp. 151-165, 2010. https://doi.org/10.1016/j.jeconom.2010.05.003

[13] Azhar Abbas Mohammad, Abduljabbar Ali Mudhir, "Dynamical approach in studying stability condition of exponential (GARCH) models," Journal of King Saud University - Science, vol. 32, no. 1, pp. 272-278, 2020. https://doi.org/10.1016/j.jksus.2018.04.028.

[14] Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle. "On the relation between the expected value and the volatility of the nominal excess return on stocks." *The Journal of Finance,* vol. 48, no. 5, pp. 1779-1801, 1993. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x

[15] Zakoian, Jean-Michel. "Threshold heteroskedastic models." *Journal of Economic Dynamics and Control,* vol. 18, no. 5, pp. 931-955, 1994. https://doi.org/10.1016/0165-1889(94)90039-6

[16] Miletić, Siniša. "Modeling and forecasting exchange rate volatility: comparison between EEC and Developed countries." *Industrija,* vol. 43, no. 1, pp. 7-24, 2015. https://doi.org/10.5937/industrija43-6612

[17] Black, Fischer. "Studies of stock market volatility changes." *Proceedings of the American Statistical Association, Business & Economic Statistics Section,* 1976.

[18] Laurent, Sébastien. "Analytical derivates of the APARCH model." *Computational Economics,* vol. 24, pp. 51-57, 2004. https://doi.org/10.1023/B:CSEM.0000038851.72226.76

[19] Engle, Robert F., and Tim Bollerslev. "Modelling the persistence of conditional variances." *Econometric Reviews,* vol. 5, no. 1, pp. 1-50, 1986. https://doi.org/10.1080/07474938608800095

[20] Granger, Clive WJ, and Ser-Huang Poon. "Forecasting

Volatility in Financial Markets: A Review (Revised Edition)." 2002. *Available at* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=331800.

[21] Timmermann, Allan. "Chapter 4 Forecast combinations." *Handbook of Economic Forecasting,* vol. 1, pp. 135-196, 2006. https://doi.org/10.1016/S1574-0706(05)01004-9

[22] Colino, Evelyn V., Scott H. Irwin, Philip Garcia, and Xiaoli Etienne. "Composite and outlook forecast accuracy." *Journal of Agricultural and Resource Economics,* vol. 37, no. 2, pp. 228-246, 2012. https://www.jstor.org/stable/23496710

[23] Diebold, Francis X., and Robert S. Mariano. "Comparing predictive accuracy." *Journal of Business & Economic Statistics,* vol. 20, no. 1, pp. 134-144, 2002. https://doi.org/10.1198/073500102753410444

[24] Mincer, Jacob A., and Victor Zarnowitz. "The evaluation of economic forecasts." In *Economic forecasts and expectations: Analysis of forecasting behavior and performance*, pp. 3-46. NBER, 1969.

[25] West, Kenneth D., and Michael W. McCracken. "Regression-based tests of predictive ability." 1998.

[26] Rossi, Barbara, and Matthieu Soupre. "Implementing tests for forecast evaluation in the presence of instabilities." *The Stata Journal,* vol. 17, no. 4, pp. 850-865, 2017. https://doi.org/10.1177/1536867X1801700405

[27] de Prince, Diogo, Pedro L. Valls Pereira, and Emerson Fernandes Marçal. "Are Professional Forecasters rational? What is the role of instability and what variables affect them?" 2022, Available at: https://ssrn.com/abstract=3545366.

[28] Preminger, Arie and Franck, Raphael. "Forecasting Exchange Rates: A Robust Regression Approach." SSRN Electronic Journal, 2005. http://dx.doi.org/10.2139/ssrn.878276.

[29] Shen, Mei-Li, Cheng-Feng Lee, Hsiou-Hsiang Liu, Po-Yin Chang, and Cheng-Hong Yang. "An effective hybrid approach for forecasting currency exchange rates." *Sustainability,* vol. 13, no. 5, pp. 1-29, 2021.