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Analyzing forecasting capabilities of GARCH models for stock prices in stochastic volatility contexts

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Abstract

Gold, a highly valued and sought-after asset, has long captured the interest of investors, financial analysts, and policymakers due to its historical significance. To predict future gold prices, this study uses the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model. The GARCH model is implemented in R Studio, and this study's findings provide valuable insights for investors, equipping them with informed decision-making capabilities and robust risk management strategies. The precise gold price forecasting achieved through the GARCH method highlights its reliability in financial prediction. This

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research also adds to the body of knowledge already available on gold price forecasting and provides a basis for investigating alternative models and incorporating macroeconomic aspects to improve prediction accuracy. Three versions of GARCH model are compared namely: GJR-GARCH, EGARCH, and standard GARCH. The implications shows that EGARCH model showed promising results, there is scope for further research and validation. Continual refinement and testing of the model's assumptions and parameters are essential to ensure its reliability and applicability in different market conditions.

Subject Classification: *68Q10.*

Keywords: *Gold price, GARCH, EHARCH and GJR GARCH.*

1. Introduction

Gold, renowned for its multifaceted attributes as a commodity, precious metal, and currency, has consistently captivated the attention of economists, investors, policymakers, and researchers worldwide. Its significance extends beyond the realm of jewelry and adornment, as it plays a pivotal role in industrial production [1]. To bolster the resilience of price data, [2] introduced a noise reduction technique founded on the wavelet transform, effectively tempering the volatility of price fluctuations. This noise reduction methodology stands as a crucial step towards enhancing the precision of subsequent predictions. Predicting the price of gold remains a paramount concern for governments, scholars, and investors alike, given its multifaceted importance. Fluctuations in mineral commodity prices, including gold, wield a profound influence on mineral investment decisions, impacting both mineral companies and resource-rich nations [3]. In the contemporary global economy, the ability to accurately forecast gold price fluctuations holds paramount importance for governments reliant on gold-based economies and investors navigating the intricacies of the commodity market. Zhao et al. [4] have elucidated those fluctuations in commodity prices, including gold, are primarily driven by shifts in oil prices, given the pervasive use of crude oil as an energy source. The intricate price mechanism governing international gold experiences a complex cycle of fluctuations occurring approximately every three months. These fluctuations are subject to the influence of various factors operating at different levels, encompassing oil prices, stock prices, and the US dollar exchange rate [5]. Gold price forecasting models aim to predict future gold prices based on various factors and historical data. These models can be broadly divided into several categories, each with its own methodology and approaches. Examples of these categories include Support Vector Machines (SVM), Neural Networks, AutoRegressive Integrated Moving Average, VAR (Vector Autoregression), Generalised Autoregressive Conditional Heteroskedasticity, and VAR. In this paper, Gold Price Forecasting is done using GARCH Model. GARCH Model: The GARCH model was suggested by [6], is used to examine the relationship between macroeconomic uncertainty and gold futures volatility. The GARCH model is an essential tool in financial econometrics for predicting and forecasting volatility in financial time series data. In our study of gold price prediction, the GARCH model plays a crucial role by capturing the inherent volatility or variance observed in daily or periodic gold returns. This is essential because the price of gold experiences varying levels of volatility over time, influenced by an array of economic and geopolitical factors. By incorporating the GARCH model, we aim to account for these fluctuations in volatility, ultimately enhancing the precision of our predictions regarding future gold prices.

The major contribution of this paper is a follow:

- The study forecasting performance of GARCH predicting gold prices.
- To extend the forecasting horizon to encompass the next ten years, allowing for ex-ante (forward-looking) predictions that provide insights into long-term price trends

2. Materials and Methods

In order to find out how macroeconomic uncertainty affects long-term gold futures volatility; this study uses a quantitative research design. The research design involves the use of the GARCH model, this aims to gain a comprehensive understanding of the relationship between macroeconomic uncertainty and gold futures volatility.

2.1. *Data Collection*

The primary data for this study is the global gold price data, which has been collected daily from January 2013 to July 2023 [7]. The data was sourced from Yahoo datasets, ensuring a wide range of observations over an extended period.

2.2. *Data Preprocessing*

To guarantee the data's feature and consistency, extensive preparation is done before feeding it into the models. This involves handling missing values, standardizing the data, and aligning the frequency of the macroeconomic variable with the daily gold price data.

2.3. *Model Evaluation and Analysis*

A few statistical measures evaluate the model's performance. Among these measurements are Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). The model performance comparison will shed light on how well each model predicts volatility in gold futures when macroeconomic uncertainty is present.

3. Empirical Results & Discussions

The conclusions are derived from fitting three distinct GARCH models to data on gold prices and extrapolating results out to a decade. Standard GARCH, GJR-GARCH (Glosten-Jagannathan-Runkle Generalised Autoregressive Conditional Heteroskedasticity), and EGARCH (Exponential Generalised Autoregressive Conditional Heteroskedasticity) are among the models.

3.1. *GARCH MODEL*

The first ADF test was performed on the original "Close" prices of the gold data. The p-value of 0.04539 indicates stationarity at a significance threshold of 0.05, thus refuting the idea that there is non-stationarity in the data. The second ADF test was performed on the differenced log returns which resulted in a lower p-value of 0.01, further supporting stationarity. Then, ARCH LM Test was performed which checks for the presence of autoregressive conditional heteroskedasticity (ARCH) effects in the residuals. We discovered that the p-value (sig. value) is less than the benchmark of 0.00, indicating the presence of strong ARCH effects. (See Table 1 and Figure 1)

Table 1

Stationarity Check

Dickey Fuller tests Statistics		**ARCH effect**
Level	First Difference	LM
0.05	0.01	0.00

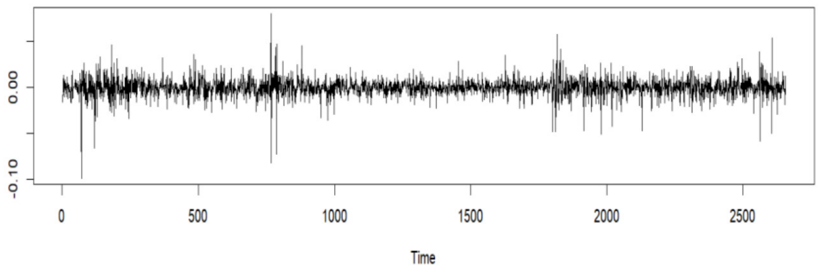


Figure 1

Time-series Plot

The GARCH model's study of the data's conditional variance dynamics produced insightful conclusions. With a mean model of ARFIMA (1,0,1), the model was developed as sGARCH (1,1) and assumed a normal distribution for the data. The model matches the data reasonably well, as shown by the log-likelihood value of 8535.568. The estimated parameters require valuable information on the behavior of the data. The parameter "mu" was estimated to be 0.000016 with a t-value of 0.094268, suggesting a small mean value for the data, although not significantly different from zero. The coefficients "ar1" and "ma1" were estimated to be 0.057353 and -0.103952, respectively, with t-values of 0.191627 and -0.348801It appears that both coefficients are around 0 and lack statistical significance, indicating that the data may not exhibit strong autoregressive or moving average behavior. The constant term in the GARCH model, "omega," is estimated at 0.000003 with a t-value of 1.105604 and indicates the initial degree of data volatility. The coefficient "alpha1" was estimated at 0.056862 with a remarkably high t-value of 11.963369, indicating a statistically significant impact on volatility. Similarly, the coefficient "beta1" was estimated at 0.918906 with an exceptionally high t-value of 138.29, suggesting a highly significant impact on conditional variance. Considering the robust standard errors, these values provide insights into the uncertainty around the parameter estimates. The standard errors for all parameters are relatively small, suggesting reasonably precise estimates. (Refer Table 2)

Table 2

Standard GARCH Model Fit

Conditional Variance Dynamics		**Log Likelihood**	**Information Criteria**
GARCH Model	sGARCH (1,1)	8535.568	Akaike: -6.4204
Mean Model	ARFIMA (1,0,1)		Bayes: -6.4072
Distribution	norm		Shibata: -6.4205
			Hannan-Quinn: -6.4156
Optimal Parameters			
Parameters	**Estimate**	**t value**	
M	0.000016	0.094268	
φ	0.057353	0.191627	
θ	-0.103952	-0.348801	
ω	0.000003	1.105604	
α	0.056862	11.963369	
β	0.918906	138.29	
Robust Standard Errors			
	Estimate	**t value**	
μ	0.000016	0.065548	
φ	0.057353	0.265936	
θ	-0.103952	-0.491292	
ω	0.000003	0.086541	
α	0.056862	0.79979	
β	0.918906	7.977671	

In summary, the GARCH model revealed valuable information about the conditional variance dynamics of the data. While some parameters were not statistically significant, others, such as “alpha1” and “beta1,” had a significant impact on volatility. The model’s log-likelihood and information criteria values further supported its overall fit to the data. In summary, the present research offers significant understanding of the data’s behavior and the primary factors causing volatility.

Weighted Ljung-Box Tests: These tests evaluate the residuals of the model’s goodness-of-fit. Table 3 shows that the residuals exhibit conditional heteroskedasticity, indicated by the low p-values from the Ljung-Box Tests applied to the squared residuals that are standardized. This suggests that the changing volatility patterns in the data may not be adequately considered by the model.

Table 3

Standardised Squared Residual Ljung-Box Tests

Lag	Statistic	p-value
Lag[1]	25.71	0.00
Lag[2*(p+q)+(p+q)-1][5]	26.28	0.00
Lag[4*(p+q)+(p+q)-1][9]	27.08	0.00

The Ljung-Box test for Lag[2*(p+q) +(p+q)-1][5] examines the autocorrelation of the squared residuals at a specific lag, calculated based on the model's parameters (p and q). The test statistic for this lag is 26.28, and the p-value of 0.00 denotes strong statistical significance. On the other hand, the Ljung-Box test for Lag[4*(p+q) +(p+q)-1][9] is comparable to the test described earlier, but it looks at autocorrelation at a different specific lag depending on the model's parameter. For this latency, the test has a value of 27.08, and the p-value of 0.00 suggests great statistical significance. This implies that the squared residuals at this lag show signs of autocorrelation as well, which strengthens the case for volatility clustering.

Weighted Arch LM Test: There is no discernible indication of conditional heteroskedasticity in the model at lags 3, 5, and 7, according to the findings of the Weighted ARCH LM Test. The test suggests that the model's residuals do not exhibit autocorrelation patterns at these lags, indicating that the assumption of constant variance over time is reasonable for the given data in table 4.

Table 4

Weighted Arch LM Test

Lag	Statistic	p-value
ARCH [3]	0.603	0.437
ARCH [5]	1.127	0.695
ARCH [7]	1.681	0.784

Nyblom Stability Test: This test checks the stability of the parameter estimates. The joint statistic is compared to asymptotic critical values. If individual statistics are greater than the critical values, it suggests parameter instability. Parameter stability is indicated by individual statistics in all three GARCH models being below the critical values. The stability of the model's estimated parameters was assessed using the Nyblom Stability Test. The joint statistic value obtained from the test was 7.5528. The test's significance is evaluated by comparing this combined statistic to the crucial values. The individual statistics for μ, φ, θ, ω, α, and β are 0.1390, 0.1463, 0.1561, 1.0935, 0.1738, and 0.1864, respectively. These individual statistics are also compared to the corresponding values. None of the individual statistics exceed the critical values, indicating that individual parameters in the model do not exhibit significant instability. (Refer table 5)

Table 5

Nyblom Stability Test

Joint Statistic	**7.5528**
Individual Statistics	
μ	0.1339
φ	0.146
θ	0.156
ω	1.09
α	0.17
β	0.186

Adjusted Pearson Goodness-of-Fit Test: Table 6 displays low p-values suggest that the GARCH models do not fit the data well, as they fail the goodness-of-fit test.

Table 6

Adjusted Pearson

Group	**Statistics**	**p value**
20	221.40	0.00
30	241.30	0.00
40	243.20	0.00
50	254.70	0.00

The results of the eGARCH (1,1) model fit for the data are given in table 7. The model is designed to capture the conditional variance dynamics, with the mean model adopting ARFIMA (1,0,1). The data distribution is assumed to be normal. A model's fit to the data is shown by its log-likelihood value, which comes in at 853.794%. The model is assessed using several information criteria, such as Hannan-Quinn, Shibata, Akaike, and Bayes. A well-fitting model is indicated by the Bayes information criterion (BIC) of -6.4006 and the Akaike information criterion (AIC) of -6.4161.

The optimal parameter estimates, and their corresponding t-values are reported. With a t-value of 0.56787 and an estimated value of 0.000026

Table 7

eGARCH Model Fit

Conditional Variance Dynamics		**Log Likelihood**	**Information Criteria**
GARCH Model	eGARCH (1,1)	8530.794	Akaike: -6.4161
Mean Model	ARFIMA (1,0,1)		Bayes: -6.4006
Distribution	norm		Shibata: -6.4161
			Hannan-Quinn: -6.4105
Optimal Parameters			
Parameters	**Estimate**	**t value**	
μ	0.000026	0.56787	
φ	0.095121	5.85568	
θ	-0.140823	-7.84063	
ω	0.267702	-21.03073	
α	0.009201	0.81733	
β	0.969482	695.10456	
γ	0.158128	10.38446	
Robust Standard Errors			
Parameters	**Estimate**	**t value**	
μ	0.000026	1.9050	
φ	0.095121	15.1953	
θ	-0.140823	-15.1818	
ω	0.267702	-58.8442	
α	0.009201	0.3724	
β	0.969482	1037.5702	
γ	0.158128	3.7363	

for the "μ" parameter, it is not statistically significant. On the other hand, the " φ " parameter has an estimated value of 0.095121, which is highly significant with a t-value of 5.85568. The " θ " parameter also shows significance, with an estimated value of -0.140823 and a t-value of -7.84063. The " ω" parameter is estimated to be 0.267702 with a highly significant negative t-value of -21.03073, indicating its importance in the model. The " α " parameter, with an estimated value of 0.009201, does not appear to be statistically significant as its t-value is 0.81733.

The " β " parameter is highly significant, with an estimated value of 0.969482 and an extraordinarily high t-value of 695.10456. Lastly, the " γ " parameter has an estimated value of 0.158128, and the t-value of 10.38446 indicates that it is statistically significant. The robust standard errors of the parameters are also provided, adding robustness to the analysis. These results offer valuable insights into the significance and impact of each parameter in the eGARCH (1,1) model, which can be further utilized for advanced analysis and modeling.

Weighted Ljung-Box Tests: The Weighted Ljung-Box test findings on the standardised squared residuals are shown in Table 8. The test is performed at different lags, and the statistics and corresponding p-values are reported. A significant p-value, typically below the 0.05 threshold, suggests that the null hypothesis can be rejected at each lag, showing that autocorrelation is present. For lag[1], the Ljung-Box statistic is 30.73, and the p-value is 0.00, indicating strong evidence of autocorrelation at lag 1. Similarly, for lag[2*(p+q)+(p+q)-1] [5], the Ljung-Box statistic is 31.21, and the p-value is 0.00, indicating significant autocorrelation at this lag as well. Lastly, at lag[4*(p+q)+(p+q)-1] [9], the Ljung-Box statistic is 31.80, and the p-value is 0.00, suggesting the presence of autocorrelation at this specific lag.

Overall, the standardized squared residuals show a large amount of autocorrelation, according to the findings of the Weighted Ljung-Box tests.

Table 8

Weighted Ljung-Box Tests on Standardized Squared Residuals.

Lag	Statistic	p-value
Lag[1]	30.73	0.00
Lag[2*(p+q)+(p+q)-1][5]	31.21	0.00
Lag[4*(p+q)+(p+q)-1][9]	31.80	0.00

Table 9

Weighted Arch LM Test

Lag	Statistic	p-value
ARCH [3]	0.508	0.477
ARCH [5]	0.895	0.764
ARCH [7]	1.256	0.8686

Weighted ARCH LM Test: Table 9 displays the results of the Weighted ARCH LM test performed at different lags. The test evaluates whether the standardized residuals of the model exhibit ARCH. For each lag, the test computes a statistic and the corresponding p-value. The test's null hypothesis is that the residuals show no evidence of the ARCH effect, which would indicate the absence of conditional heteroskedasticity. On the other hand, if the significant p-value was less than the significance level of 0.05, the presence of the ARCH effect and conditional heteroskedasticity in the residuals would imply that the null hypothesis is rejected.

At ARCH lag [3], the computed statistic is 0.508, and the related p-value is 0.477. This suggests that the null hypothesis cannot be ruled out because there is no meaningful evidence of the ARCH effect at this latency. Likewise, the p-value is 0.764 and the statistic is 0.895 at ARCH lag [5]. Once more, the data do not demonstrate a meaningful ARCH effect at this lag, so the null hypothesis cannot be ruled out.

Finally, the p-value is 0.8686 and the statistic is 1.256 at ARCH lag [7]. These results also suggest no significant evidence of ARCH effect at this lag, and the null hypothesis cannot be rejected. Overall, based on the Weighted ARCH LM test results, there is no significant evidence of conditional heteroskedasticity in the model's standardized residuals at any of the tested lags. This indicates that the model's residuals do not exhibit ARCH patterns, implying that the assumption of constant conditional variance holds reasonably well.

Nyblom Stability Test: The test computes a statistic and the corresponding p-value. The test's null hypothesis is that the residuals show no evidence of the ARCH effect, which would indicate the absence of conditional heteroskedasticity. Conversely, a substantial p-value would imply the elimination of the null assumption and show that the residuals contain the ARCH effect and conditional heteroskedasticity. At ARCH lag [3], the computed statistic is 0.508, and the associated p-value is 0.477. This

Table 10

Nyblom Stability Test

Joint Statistic	**1.3317**
Individual Statistics	
Μ	0.106
Φ	0.210
Θ	0.216
Ω	0.229
Α	0.425
Β	0.236
Γ	0.092

suggests that the null hypothesis cannot be ruled out because there is no meaningful evidence of the ARCH effect at this latency.

The statistic and p-value are 0.895 and 0.764, respectively, at ARCH lag [5]. Lastly, at ARCH lag [7] [8] [9] [10], the statistic is 1.256, and the p-value is 0.8686. These results also suggest no significant evidence of ARCH effect at this lag, and the null hypothesis cannot be rejected. (Table 10)

Adjusted Pearson Goodness-of-Fit Test: The model exhibits an extremely good fit to the data for each of the analyzed groups, according to the findings of the test [11]. The low p-values suggest that the model is a suitable representation of the data and provides a good fit to the observed values in each group. (Refer Table 11)

Table 11

Adjusted Pearson

Group	**Statistics**	**p value**
20	219.2	0.00
30	234.5	0.00
40	252.4	0.00
50	257.5	0.00

The financial time series has been fitted with the gjrGARCH model, and the obtained parameters show the presence of conditional volatility clustering. The highly significant t-values for alpha1 and beta1 suggest

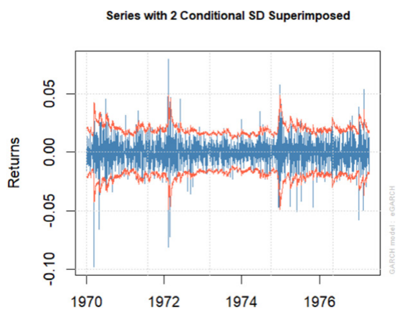


Figure 2

(a) The gjrGARCH model Series

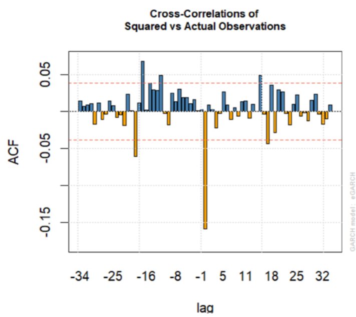


Figure 2

(b) The gjrGARCH model Square and Actual Observations

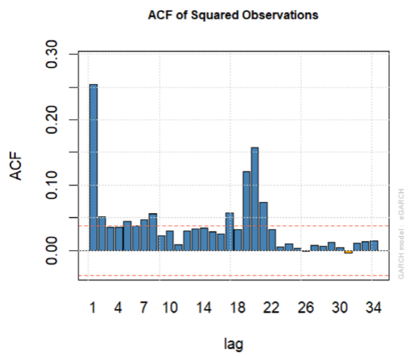


Figure 2

(c) The gjrGARCH model ACF

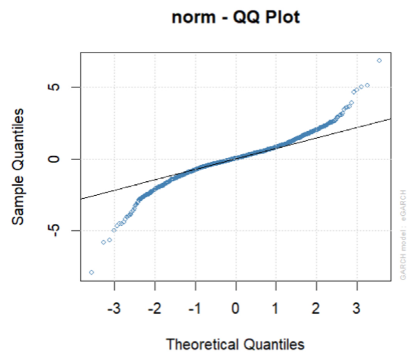


Figure 2

(d) The gjrGARCH model results QQ Plot

that the asymmetric effect is significant, which is common in financial data where volatility tends to increase more after negative shocks compared to positive shocks. However, the significance of other parameters needs further investigation to determine their impact on the model's fit and the underlying data dynamics. (Refer Figure 2 and Table 12),

Weighted Ljung-Box Tests: All three lag orders (1, 5, and 9) have p-values of 0.00, which indicates that they are far below the traditional significance level of 0.05 and extremely near to zero. The null hypothesis that the squared residuals show no autocorrelation is strongly refuted by this. Consequently, there is a strong serial correlation seen in the model's

Table 12

The gjrGARCH Model Fit

Conditional Variance Dynamics		**Log Likelihood**	**Information Criteria**
GARCH Model	gjrGARCH (1,1)	8535.953	Akaike: -6.420
Mean Model	ARFIMA (1,0,1)	-	Bayes: -6.404
Distribution	Norm	-	Shibata: -6.420
			Hannan-Quinn: -6.414
Optimal Parameters			
Parameters	**Estimate**	**t value**	
μ	0.000047	0.27628	
φ	0.036798	0.12186	
θ	-0.08271	-0.27407	
ω	0.000003	0.54242	
α	0.062707	24.18857	
β	0.919183	49.73903	
γ	-0.01094	-1.02968	
Robust Standard Errors			
Parameters	**Estimate**	**t value**	
μ	0.000047	0.076297	
φ	0.036798	0.09205	
θ	-0.08271	-0.23283	
ω	0.000003	0.020427	
α	0.062707	0.217441	
β	0.919183	1.783415	
γ	-0.01094	-0.06788	

residuals, indicating that the conditional volatility patterns in the data may not have been adequately captured by the model. (See Table 13)

Weighted ARCH LM Test: All lag orders (3, 5, and 7) have published p-values, and They are all more than the usual 0.05 significance level. This suggests that the null hypothesis, according to which the residuals do not show conditional heteroskedasticity, cannot be rejected because the p-values are not statistically significant. In other words, the model appears to adequately capture the time-varying variance of the residuals, and there is no significant evidence of ARCH effects. (Refer Table 14)

Nyblom Stability Test: The Joint Statistic is reported as 10.08. This value represents the overall test statistic for the stability of all parameters collectively. To assess the significance of this statistic, it can be compared

Table 13

Weighted Ljung-Box Tests on Standardized Squared Residuals.

Lag	Statistic	p-value
Lag[1]	25.22	0.00
Lag[2*(p+q)+(p+q)-1][5]	25.77	0.00
Lag[4*(p+q)+(p+q)-1][9]	26.51	0.00

Table 14

Weighted Arch LM Test

Lag	Statistic	p-value
ARCH [3]	0.567	0.451
ARCH [5]	0.078	0.709
ARCH [7]	1.578	0.805

to critical values. However, the table 15 does not provide critical values for this test. For every parameter that the model estimates (mu, ar1, ma1, omega, alpha1, beta1, and gamma1), the Individual Statistics are given. These statistics evaluate the stability of each parameter individually.

Adjusted Pearson Goodness-of-Fit Test: The results of the this test show that for each of the analyzed groups, the model shows an exceptionally strong fit to the data. The low p-values suggest that the model is a suitable representation of the data and provides a good fit to the observed values in each group. (Refer Table 16)

Table 15

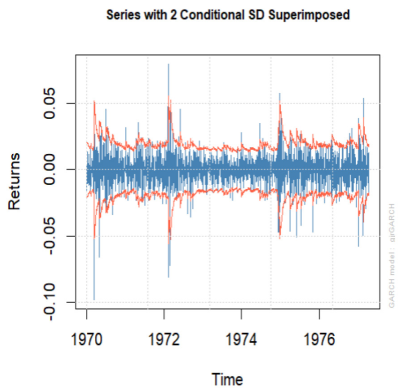
Nyblom Stability Test

Joint Statistic	**10.08**
Individual Statistics	
μ	0.168
φ	0.150
θ	0.158
ω	0.192
α	0.205
β	0.197
Γ	0.330

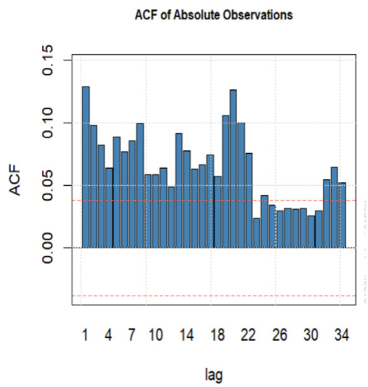
Table 16

Adjusted Pearson.

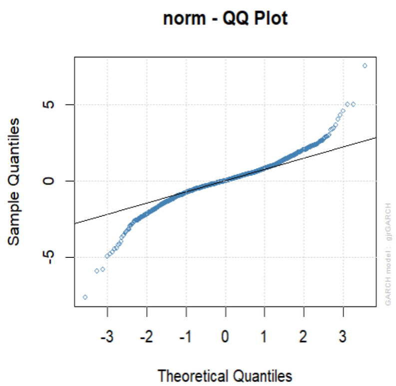
Group	Statistics	p value
20	225.8	0.00
30	236.3	0.00
40	251.1	0.00
50	250.7	0.00



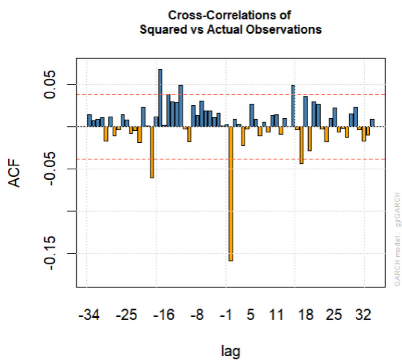
(a) The GARCH model



(b) The GARCH model ACF



(c) The GARCH model QQ Plot



(d) The GARCH model Cross Correlation

Figure 3

Table 17 provides the GARCH model forecast for a specific time horizon using the sGARCH (1,1) model (Figure 3). The forecast is made for ten time periods ahead, and it includes predicted values for both the series and the standard deviation with conditions (sigma). The forecasted values are given for the series and the standard deviation with conditions (sigma) for each of the ten periods ahead (T+1 to T+10). The series represents the predicted values for the underlying variable, while sigma represents the forecasted conditional volatility or uncertainty in the predictions. For instance, At T+1, the forecasted series value is -5.864e-04, and the forecasted sigma (conditional standard deviation) is 0.009647. At T+2, the forecasted series value is -1.857e-05, and the forecasted sigma is 0.009671 and the pattern continues for the subsequent periods (T+3 to T+10).

Table 17

Forecasted Values

	Series	Sigma
T+1	-5.86E-04	0.009647
T+2	-1.86E-05	0.009671
T+3	1.40E-05	0.009694
T+4	1.59E-05	0.009717
T+5	1.60E-05	0.009739
T+6	1.60E-05	0.00976
T+7	1.60E-05	0.009781
T+8	1.60E-05	0.009801
T+9	1.60E-05	0.009821
T+10	1.60E-05	0.00984
Horizon:	10	
0-roll	Forecast	[T0=1977-04-11

The defined evaluation metrics used here are a Mean Squared Error (MSE) and Mean Absolute (MSA). Table 18 “Evaluation Metrics” presents the evaluation results for the forecast accuracy of the GARCH model. It includes two evaluation metrics in Table 18 [12].

Mean Squared Error (MSE): The average squared projected error is determined by the MSE. It is employed to evaluate the forecast errors’ variance. In this case, the MSE value is 3,831,690, indicating the model’s squared average forecast error.

Table 18

Forecasted Values

Metrics	Value
MSE	3831690
MSA	1957.4

Mean Absolute Error (MAE): The MAE is a representation of the average of the absolute predicted errors. It does not consider the direction of the forecast errors; instead, it measures their size. Here, the MAE value is 1,957.4, indicating the model's average absolute forecast error.

When evaluating the forecast accuracy and dependability of the GARCH model, several evaluation measures are crucial. Reduced MSE and MAE values indicate better forecast performance since they show a reduced error between the values that the model predicts and the actual values that were observed.

4. Conclusion

The direct comparison of different models emphasizes how crucial it is to select the best model for volatility research and gold price forecasting. The eGARCH model stands out due to its significant parameters and robust insights into volatility patterns. However, it's crucial to emphasize that a quantitative comparison of their forecasting performance, such as Mean Squared Error (MSE) or other relevant metrics, is essential to draw a definitive conclusion regarding their relative performance.

The study's findings underscore the significance of advanced conditional variance models, particularly the eGARCH model, in comprehending financial time series data and improving risk management and investment strategies. Further research should focus on quantitative evaluations to validate these models' predictive accuracy and reliability in real-world scenarios.

In our study, the outcomes are categorized into two main components: forecasting prices (returns) and predicting standard deviation (variance). The primary goal of our analysis was to enhance our understanding of both the price movements and the volatility dynamics of financial assets, with a focus on gold prices. The outcomes related to forecasting prices, or returns, provide insights into the future direction of asset prices. We utilized several models, including GARCH, EGARCH, and GJR-GARCH, to estimate potential changes in prices over time. These models help us anticipate the potential magnitude and direction of price changes, aiding investors and analysts in making informed decisions regarding their investment strategies.

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Conflicts of Interest

The authors declare no conflicts of interest.

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