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A Comparison of Volatility Forecasting of Major Macro Economic Indicators

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Abstract

Volatility plays a significant role in forecasting because of its abrupt nature. In this paper, few volatility models like ARCH, GARCH, EGARCH, GJR – GARCH have been studied and compared for major Macroeconomic indicators like BSE Indices (India), Govt Bond Yield (India), CPI (India), Exchange Rate (INR / USD), GDP of US (USA), US Corporate Bond Yield (USA), USCPI Urban (USA) and US Interest Rate (USA).

Keywords: *Time Series, Forecasting, Volatility, ARCH, GARCH, EGARCH, GJR-GARCH*

1. Introduction

1.1. Overview

Volatility (abbreviated "σ") in finance refers to the degree of variation in a trading price series over time, typically measured by the standard deviation of logarithmic returns. Historic volatility is a time series of historical market prices. Implied volatility is generated from the market price of a market-traded derivative, namely an option. Financial analysis now incorporates risk management and regulatory considerations. Investors have varying risk tolerance levels. Volatility is not synonymous with risk, despite being viewed as such. There are various meanings of volatility. In finance, volatility refers to the variation of a financial asset over time as measured by its standard deviation of returns. The danger of asset value changes. High volatility indicates a significant predicted shift in the security, whereas low volatility suggests a less drastic change.

In fact, volatility cannot be directly observed and must be calculated using an asset's underlying price. The fascinating aspect of calculating volatility using asset returns as the underlying series is that volatility exhibits four common properties (Tsay, 2013). (1) The series' variance varies between high and low points over time, resulting in "volatility clusters". (2) Volatility jumps are uncommon because volatility evolves in a consistent manner. (3) Volatility varies within a specific range and does not converge to infinity. (4) Large price declines appear to have a greater impact on volatility than equal-sized price increases, indicating asymmetric impacts. The fourth characteristic, known as the "leverage effect," is commonly observed in financial time series (Mandelbrot, 1963; Black, 1976). These four phenomena, which have been discovered to characterize the movement of volatility in financial time series, have played an important role in the development of volatility forecasting models (Tsay, 2013).

Previous theoretical models of volatility assumed constant variance (Merton, 1969; Black and Scholes, 1973). These models, such as homoscedastic regression, may not accurately represent volatility. To better express volatility features

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in models, Engle (1982) created the Autoregressive Conditional Heteroscedasticity (ARCH) model. Unlike standard constant variance models, the ARCH process makes use of lagged disturbances to account for the time-varying conditional variance of financial time series. The ARCH's shortcoming was that it required many parameters to represent the dynamics of conditional variance. Bollerslev (1986) proposed the Generalized ARCH (GARCH), a more flexible lag structure that reduces the number of model parameters. Both the ARCH and GARCH models can represent the widely observed volatility clustering and leptokurtosis. The problem of these models is that they do not capture the leverage effect because they are symmetric. Many asymmetric extensions to GARCH have since been proposed to solve the issue that a negative shock in asset returns has a greater influence on the series' volatility than an equally significant positive shock (Tsay, 2013). Examples of asymmetric extensions include Nelson's Exponential GARCH (EGARCH) and Glosten-Jaganathan-Runkle (GJR).

This study examines the volatility forecasting performance of symmetric and asymmetric GARCH models on macroeconomic data. ARCH (1), ARCH (2), ARCH (3), GARCH (1,1), GARCH (1,2), EGARCH (1,1), EGARCH (1,2), and GJR-GARCH (1,1,1) have been examined for the eight datasets in this study.

2. Literature Review

There have been numerous earlier articles on the forecasting performance of GARCH models. Research suggests that QGARCH is the best model for forecasting stock return volatility in Sweden, Italy, Germany, and Spain (Franses and Van Dijk, 1996), while GJR is better for forecasting volatility in an Australian index (Brailsford and Faff, 1996), the DJ composite index is difficult to forecast with a single GARCH specification (Brooks, 1998), and EGARCH may be more useful for forecasting two Tel Aviv indices. The results, as shown, are contradictory. Volatility is a stock variable that accumulates over time. The frequency of data collection (minutely, hourly, daily, etc.) affects the results. The frequency of data can significantly enhance volatility estimations and forecasts (Fung and Hsieh, 1991; Andersen and Bollerslev, 1998). The trade-off is that using too much frequency can result in misleading regression. Poon and Granger find that some previous research was conducted on nonstationary series, which contradicts the forecasts because the models presuppose stationary series.

Another intriguing result from earlier research is that the model with the best in-sample fit does not always provide the best out-of-sample forecast. It is statistically necessary to correctly specify the lag order, conditional mean process, and error term distribution to reflect the series' historical movements; however, because the future is unknown, the best-fitted model does not always produce the best forecast (Shamiri and Isa, 2009). Previous research has also discovered that the shortest lag order is appropriate for capturing changing volatility and so providing satisfactory findings (Gokcan, 2000; Javed and Mantalos, 2013). Because of this, the shortest lag order is commonly used for forecasting with GARCH models (Teräsvirta, 2006).

3. Volatility Models

3.1. ARCH Model

In econometrics, the autoregressive conditional heteroscedasticity (ARCH) model describes the variance of the current error term or innovation as a function of the actual sizes of the previous time periods' error terms; the variance is frequently related to the squares of the previous innovations. When the error variance in a time series follows an autoregressive (AR) model, the ARCH model is appropriate.

ARCH models are commonly used to model time-varying volatility and volatility clustering, which is defined as swings interspersed with periods of relative calm. The volatility at time 't' is completely pre-determined (deterministic) given previous values, so ARCH-type models are not in the family of stochastic volatility models.

Let ε_t denote the error terms to model a time series using an ARCH process. These ε_t are split into a stochastic piece z_t and a time-dependent standard deviation σ_t characterizing the typical size of the terms so that $\varepsilon_t = \sigma_t z_t$.

The series σ_t^2 is modelled by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}{}^2 + \dots + \alpha_q \varepsilon_{t-q}{}^2 \text{ where } \alpha_0 > 0,\ \alpha_i > 0$$

3.2. GARCH Model

The generalised autoregressive conditional heteroskedasticity (GARCH) approach describes a method for estimating market volatility. When attempting to predict the prices and rates of financial instruments, financial professionals frequently prefer the GARCH process over other models.

Heteroskedasticity is a statistical term that describes the irregular pattern of variation of an error term or variable in a statistical model. Observations do not follow a linear pattern when there is heteroskedasticity. Instead, they tend to congregate.

As a result, the model's conclusions and predictive value will be untrustworthy. GARCH is a statistical model that can be used to analyse various types of financial data, such as macroeconomic data. This model is commonly used by financial institutions to estimate the volatility of returns on stocks, bonds, and market indices. They use the resulting data to determine pricing, determine which assets are likely to provide higher returns, and forecast the returns of current investments to aid in asset allocation, hedging, risk management, and portfolio optimization decisions.

GARCH(p, q) is modelled by

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_p \sigma_{t-p}^2$$

3.3. EGARCH Model

Nelson proposed the EGARCH model in 1991. The nonnegativity constraints in the linear GARCH model, according to Nelson and Cao (1992), are overly restrictive. The GARCH model imposes nonnegative constraints on the parameters, whereas the EGARCH model imposes no constraints on these parameters. In the EGARCH model, the conditional variance is an asymmetric function of lagged disturbances. It is a dynamic model that addresses conditional heteroscedasticity, or volatility clustering, in the process of innovation. When an innovation process does not exhibit significant autocorrelation, but the variance of the process changes over time, volatility clustering occurs. It is popular for a variety of reasons, including the ability to capture both asymmetries, or the different effects on conditional volatility of positive and negative effects of equal magnitude and leverage, or the negative correlation between return shocks and subsequent volatility shocks.

EGARCH is modelled by

$$\log \sigma_t^2 = \omega + \sum_{k=1}^{q} \beta_k \, g(Z_{t-k}) + \sum_{k=1}^{p} \alpha_k \log \sigma_{t-k}^2$$

where $g(Z_t) = \theta Z_t + \lambda(IZ_tI - E(IZ_tI))$, σ_t^2 is the conditional variance and $\omega, \theta, \lambda, \alpha, \beta$ are the parameters.

3.4. GJR – GARCH Model

The Glosten, Jagannathan, and Runkle-GARCH (GJR - GARCH) model is the fourth model. It differs from the original GARCH model in that it does not assume that, in the event of a shock, the shock's sign would be unrelated to the response variable. It would just depend on how big the shock was.

The GJR GARCH model is represented by the expression

$$\tau_t^2 = \omega + \sum_{i=1}^{\rho} \alpha_i \in_t^2 + \sum_{j=1}^{q} \beta_j \ \sigma_{t-j}^2 + \sum_{i=1}^{p} \gamma_i I_{t-1} + \sigma_{t-i}^2$$

4. Error Metrics

4.1. Root Mean Squared Error (RMSE)

It is a commonly used metric for comparing the predicted values (sample or population values) with the values observed by a model or estimator. The RMSE is defined as the square root of the second sample moment of the differences between predicted and observed values, or the quadratic mean of these differences. When the computations are performed over the data sample that was used for estimate, these deviations are referred to as residuals, and when they are computed out-of-sample, they are referred to as errors (or prediction errors). The RMSE is always positive, and a value of 0 (which is nearly never reached in practice) indicates that the data is perfectly suited. A lower RMSE is often preferable than a greater one. However, because the measure is dependent on the scale of the numbers used, comparisons between different types of data would be invalid.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \bar{x}_i)}{N}}$$

where

$RMSE$ = Root Mean Squared Error

N = the number of data points

x_i = actual observations

$\bar{x}_i$ = predicted observations

4.2. Mean Absolute Error (MAE)

It is a metric for comparing errors between paired observations describing the same occurrence.

$$MAE = \frac{\sum_{i=1}^{N} |x_i - \bar{x}_i|}{N}$$

where

MAE = Mean Absolute Error

N = the number of data points

x_i = actual observations

$\bar{x}_i$ = predicted observations

4.3. Mean Absolute Percentage Error (MAPE)

It's a statistical gauge of how accurately a forecasting technique predicts the future. When x_i and $\bar{x}_i$ represent the actual and projected values, respectively, the accuracy is often stated as a ratio determined by the formula. Divided by the actual value of x_i is the difference between them. The absolute value of this ratio is multiplied by the number of fitted points, n, for each projected point in time.

$$MAPE = \frac{\sum_{i=1}^{N} \left| \frac{x_i - \bar{x}_i}{x_i} \right|}{N}$$

where

N = the number of data points

x_i = actual observations

$\bar{x}_i$ = predicted observation

5. Findings of the Study

This section presents experimental results on the performance of the various volatility models like ARCH, GARCH, EGARCH and GJR – GARCH for all the 8 datasets.

For conducting the experiments, I took Log Return of the series of the 8 datasets, assumed the mean to be "constant" and computed for three distributions namely "normal", "t" and "skew t".

The model with the lowest BIC has been selected along with the errors namely Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE).

The results of ARCH (1), ARCH (2), ARCH (3), GARCH (1,1), GARCH (1,2), EGARCH (1,1), EGARCH (1,2) and GJR-GARCH (1,1,1) for the 8 datasets are as follows:

1. BSE Dataset

As we can see from the Table 1, that for the BSE dataset, the lowest BIC happens to be from EGARCH (1,1) and "skew t "distribution with a BIC value of 1010.72 and the corresponding error values are as follows

Table 1: BIC Values of the BSE Dataset

BIC BSE	Normal	*t*	Skewt
ARCH (1)	1048.15	1024.97	1020.92
ARCH (2)	1049.69	1028.12	1022.27
ARCH (3)	1049.20	1032.24	1023.84
GARCH (1,1)	1031.14	1017.29	1012.12

Table 1 (Cont.)			
BIC BSE	Normal	t	Skewt
GARCH (1,2)	1037.14	1022.77	1017.18
EGARCH (1,1)	1028.92	1016.04	1010.72
EGARCH (1,2)	1034.81	1021.78	1016.22
GJRGARCH (1,1,1)	1028.72	1018.12	1011.17

Mean Absolute Error (MAE): 1.042

Root Mean Squared Error (RMSE): 2.047

2. CPI Dataset

As we can see from the Table 2, that for the CPI dataset, the lowest BIC happens to be from ARCH (1) and “t “distribution with a BIC value of 861.85 and the corresponding error values are as follows

Table 2: BIC Values of the CPI Dataset			
BIC CPI	Normal	t	Skewt
ARCH (1)	882.79	861.85	867.72
ARCH (2)	888.67	867.74	873.61
ARCH (3)	894.56	873.63	879.51
GARCH (1,1)	888.65	868.89	874.62
GARCH (1,2)	890.79	873.31	879.11
EGARCH (1,1)	889.26	870.36	876.01
EGARCH (1,2)	890.09	874.37	880.09
GJRGARCH (1,1,1)	882.77	867.37	872.91

Mean Absolute Error (MAE): 0.749

Root Mean Squared Error (RMSE): 1.358

3. Exchange Rate Dataset

As we can see from the Table 3, that for the Exchange Rate dataset, the lowest BIC happens to be from EGARCH (1,1) and “t “distribution with a BIC value of 1270.48 and the corresponding error values are as follows

Table 3: BIC Values of the Exchange Rate Dataset			
BIC Exchange Rate	Normal	t	Skewt
ARCH (1)	1388.27	1324.41	1328.66
ARCH (2)	1384.31	1319.74	1325.13
ARCH (3)	1382.17	1322.55	1328.32
GARCH (1,1)	1365.11	1289.65	1294.31
GARCH (1,2)	1370.77	1295.44	1300.11
EGARCH (1,1)	1365.91	1270.48	1276.27
EGARCH (1,2)	1371.69	1276.28	1282.07
GJRGARCH (1,1,1)	1361.02	1293.71	1298.53

Mean Absolute Error (MAE): 55.188

Root Mean Squared Error (RMSE): 70.238

4. Govt. Bond Yield Dataset

As we can see from the Table 4, that for the Govt. Bond Yield dataset, the lowest BIC happens to be from EGARCH (1,1) and "t "distribution with a BIC value of 1699.28 and the corresponding error values are as follows

Table 4: BIC Values of the Govt. Bond Yield Dataset

BIC Govt Bond Yield	Normal	*t*	Skewt
ARCH (1)	2033.38	1711.04	1716.82
ARCH (2)	1813.37	1709.86	1715.55
ARCH (3)	1817.08	1711.89	1717.45
GARCH (1,1)	1880.96	1706.47	1712.06
GARCH (1,2)	1886.76	1712.27	1717.86
EGARCH (1,1)	1863.12	1699.28	1704.77
EGARCH (1,2)	1890.12	1704.73	1710.16
GJRGARCH (1,1,1)	1835.95	1712.2	1717.81

Mean Absolute Error (MAE): 112.171

Root Mean Squared Error (RMSE): 1091.424

5. USGDP Dataset

As we can see from the Table 5, that for the USGDP dataset, the lowest BIC happens to be from GARCH (1,1) and "t "distribution with a BIC value of 866.77 and the corresponding error values are as follows

Table 5: BIC Values of the USGDP Dataset

BIC USGDP	Normal	*t*	Skewt
ARCH (1)	909.43	877.67	882.71
ARCH (2)	912.47	876.45	882.08
ARCH (3)	904.17	876.04	881.31
GARCH (1,1)	900.81	866.77	871
GARCH (1,2)	900.15	870.1	874.65
EGARCH (1,1)	884.61	863.6	868.57
EGARCH (1,2)	880.64	865.11	870.44
GJRGARCH (1,1,1)	899.53	872.39	876.35

Mean Absolute Error (MAE): 2.098

Root Mean Squared Error (RMSE): 8.378

6. US Corporate Bond Yield Dataset

As we can see from the Table 6, that for the US Corporate Bond Yield dataset, the lowest BIC happens to be from ARCH (1) and "t" distribution with a BIC value of 1889.39 and the corresponding error values are as follows:

Table 6: BIC Values of the US Corporate Bond Yield Dataset			
BIC US Corporate	**Normal**	***t***	**Skewt**
ARCH (1)	1937.05	1889.39	1894.35
ARCH (2)	1930.61	1893.81	1898.95
ARCH (3)	1927.07	1895.12	1899.90
GARCH (1,1)	1921.73	1890.61	1895.44
GARCH (1,2)	1927.61	1893.38	1896.08
EGARCH (1,1)	1924.98	1891.14	1895.71
EGARCH (1,2)	1930.86	1895.05	1898.23
GJRGARCH (1,1,1)	1927.58	1896.12	1900.62

Mean Absolute Error (MAE): 16.1

Root Mean Squared Error (RMSE): 38.425

7. US Interest Rate Dataset

As we can see from the above Table 7, that for the US Interest Rate dataset, the lowest BIC happens to be from GJR GARCH (1,1,1) and "skew t" distribution with a BIC value of -171.20 and the corresponding error values are as follows

Table 7: BIC Values of the US Interest Rate Dataset			
BIC US Interest Rate	**Normal**	***t***	**Skewt**
ARCH (1)	2996.61	385.99	299.56
ARCH (2)	2931.44	1055.19	5.68
ARCH (3)	2937.33	1062.25	155.92
GARCH (1,1)	2979.12	755.59	340.45
GARCH (1,2)	2899.21	628.89	322.21
EGARCH (1,1)	2810.73	–46.97	32.11
EGARCH (1,2)	2949.68	–36.92	119.19
GJRGARCH (1,1,1)	2954.32	374.81	–171.20

Mean Absolute Error (MAE): 241.917

Root Mean Squared Error (RMSE): 2365.493

8. USCPI Urban Dataset

As we can see from the Table 8, that for the USCPI Urban dataset, the lowest BIC happens to be from ARCH (1) and "normal "distribution with a BIC value of -162.185 and the corresponding error values are as follows

Table 8: BIC Values of the USCPI Urban Dataset			
BIC USCPI Urban	**Normal**	***t***	**Skewt**
ARCH (1)	-162.185	-156.86	-151.19
ARCH (2)	-160.621	-154.60	-148.74

Table 8 (Cont.)			
BIC USCPI Urban	**Normal**	***t***	**Skewt**
ARCH (3)	-154.74	-148.77	-142.70
GARCH (1,1)	-160.13	-154.00	-148.10
GARCH (1,2)	-154.25	-148.09	-142.38
EGARCH (1,1)	-161.49	-155.47	-149.41
EGARCH (1,2)	-155.61	-149.63	-143.69
GJRGARCH (1,1,1)	-154.91	-148.67	-143.06

Mean Absolute Error (MAE): 0.035

Root Mean Squared Error (RMSE): 0.053

6. Conclusion

For the volatility models, ARCH (1), ARCH (2), ARCH (3), GARCH (1,1), GARCH (1,2), EGARCH (1,1), EGARCH (1,2) and GJR-GARCH (1,1,1) models have been examined for all the 8 datasets. While analyzing, different results have come across. For the BSE dataset, EGARCH(1,1) with “skew t” distribution outperformed others, for the CPI dataset ARCH(1) with “t” distribution outperformed others, for the Exchange Rate dataset, EGARCH(1,1) with “t” distribution outperformed others, for the Govt. Bond Yield dataset, EGARCH(1,1) with “t” distribution outperformed others, for the USGDP dataset, GARCH (1,1) with “t” distribution outperformed others, for the US Corporate Bond Yield dataset, ARCH (1) with “t” distribution outperformed others, for the US Interest Rate dataset, GJR-GARCH (1,1,1) with “skew t” distribution outperformed others whereas for the USCPI Urban dataset, ARCH (1) with “normal distribution” outperformed others.

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