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Forecasting Volatility of Asset Price

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Abstract

The movements of asset prices are very complex and therefore seem to be unpredictable. However, one of the major challenges of econometrics is how to forecast such an apparently unpredictable economical series. This paper investigates forecasting methods for assets prices and determines the optimal model for each asset price; gold and crude oil are used as assets. The forecasting technique used is: ARCH family models, such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH). Analysis of the two ARCH family models were conducted, the two test parameters used are Akaike Information Criterion (AIC) and Schwartz Information Criterion (SIC). The guiding principle is, the lower the values of AIC and SICS, the better the model of the asset. Eventually, the study shows that gold has a better forecasting model and EGARCH model is the best forecasting model fit for both gold and oil. Moreover, gold has strong market value and ability to withstand stress during economic recession.

1. Introduction

Forecasting is fundamental to the risk management process to price assets derivatives, hedging strategies and estimating the financial risk of a firm. In recent years, Autoregressive Conditional Heteroscedasticity (ARCH) type models have become popular as a means of capturing characteristics of financial returns like thick tails and volatility clustering. These models use time series data on returns to model conditional variance. An alternative way to estimate future volatility is to use options prices, which reflect the market expectation of volatility. Analytical option pricing models can be used to back out implied volatility over the remaining life of the option given the observed market price. In the construction of volatility forecasts, energy market participants would like to know which model produces the most accurate forecasts, as well as, whether the complex time series models enhance any significant volatility information beyond what contained in option prices.

[1] compared the relative information content and predictive power of implied volatility and ARCH family forecasts for asset futures. A similar study by [2] studied analysis for financial management of efficiency of options market in predicting volatility. [3] examined the prediction of financial volatilities for crude oil, gold and natural gas markets. Finance is focused on intertemporal decision making under uncertainty and so forecasts of unknown future outcomes is integral to several areas of finance asset pricing requires forecasts of future cash. Risk management relies on forecasts of variances and covariance of returns on portfolios that frequently comprise large numbers of assets.

Countless studies in corporate finance analyze firms' capital budgeting decisions which in turn depend on projected cash flows and firms forecasts of the costs and benefits of issuing debt and equity. A large literature in banking analyzes the possibility of runs which reflects investors forecasts of both a bank's solvency and liquidity as well as their expectation of other agents (depositors) decisions on whether to run or stay put. While economics and financial forecasting share many methods and perspectives, some important features help differentiate the two areas competitive pressures and market efficiency mean that the signal-to-noise ratio in many financial forecasting problems particularly predictability of asset returns is very low compared to standard forecasting problems in macroeconomics in which the presence of a sizeable persistent component makes forecasting easier. The presence of weak predictors with low predictive power and the resulting importance of parameter estimation error is therefore the norm rather than the exception in financial forecasting. The possibility of readily trading on price forecasts makes the scope for feedback effective from forecasts to actual outcomes stronger in finance than in other areas of economics.

Model instability is therefore particularly important to financial forecasting; overstating and issues related to data mining have increasingly become a concern in financial forecasting due to the ease with which numerous forecasting models can be fitted to a given data set and the difficulty of generating new and genuinely independent data sets on which to test the forecasting performance. How should the performance of a forecasting model be evaluated when this model is selected as the best performer among a larger set of competing specifications? This situation generates a multiple hypothesis testing problem that, if not accounted for, can lead to findings of spurious predictability patterns and serious distortions in inference while volatility forecasting also features prominently in forecasting of macroeconomic variables. The risk management is concerned with forecasting the correlations between very large sets of variables and so gives rise to high dimensional forecasting problems. Moreover, access to high frequency data, sampled every few seconds during trading sessions for the most liquid assets, means that measures of realized variances can be constructed and used to forecast future risks. This type of data does not, yet, have obvious counterparts in economics where measurements tend to be conducted at a lower frequency.

The Akaike information criterion (AIC) is an estimator of out-of-sample prediction error and thereby relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Thus, AIC provides a means for model selection. In estimating the amount of information lost by a model, AIC deals with the trade-off between the goodness of fit of the model and the simplicity of the model. In other words, AIC deals with both the risk of over fitting and the risk of under fitting. The Schwarz information criterion (SIC) is one of the most widely known and used tools in statistical model selection. The criterion was derived by Schwarz in 1978 to serve as an asymptotic approximation to a transformation of the Bayesian posterior probability of a candidate model. Although the original derivation assumes that the observed data is independent, identically distributed, and arising from a probability distribution in the regular exponential family, SIC has traditionally been used in a much larger scope of model selection problems. To better justify the widespread applicability of SIC, and then derive the criterion in a very general framework: one which does not assume any specific form for the likelihood function, but only requires that it satisfies certain non-restrictive regularity conditions. In this study, AIC and SIC are used to determine the best model in the ARCH Family model, the lower the values of AIC and SIC, the better the model. The remaining parts of this paper is organized as follow: section two reviews literature, section three explains the methodology, results and discussions are considered in section four while section five concludes the paper.

2. Literature Review

Economists have long thought that forecasts are potentially useful as decision aids and have devoted considerable efforts to develop and assess forecasting methods [4]. Forecasts can provide decision makers with technical and market support to help execute policies. In stock markets, forecasts are typically made for the prices of assets commodity outputs. Less work has been done on forecasting the primary inputs needed to produce the commodities. However, the most important variable inputs are crude oil and gold, since crude oil and gold are used as measurement in stock market [5]. With the recent price volatility in the fuel market, making wrong decisions in fuel purchasing can have a significant impact on the bottom line for farming firms or fuel providers. While the ability to anticipate short-term fuel prices may be useful, very little work has been done to evaluate the ability to forecast assets prices.

The dearth of research on this topic requires examining the energy forecasting literature to design an approach to forecast assets prices. [6] in his work titled, Bias Correction effect of the AIC for selecting variables in Normal Multivariate Linear Regression models. He considered two criteria: The Akaike Information Criterion, AIC and Takeuchi Information Criterion TIC. In his paper he also compared the performance of AIC and Akaike Information Criterion Component, AICC. Both criteria may be viewed as estimators of the expected Kullback Leibler information. The bias of AIC and AICC are studied in the under fitting case, where none of the candidate models includes the true model [6]. Both normal linear regression and autoregressive candidate models are considered. The bias of AICC is typically smaller, often dramatically smaller, than that of AIC. A simulation study in which the true model is an infinite order auto regression shows that, even in moderate sample sizes, AICC provides substantially better model selections than AIC.

[7] in their work titled; Forecasting of crude oil price, said as most important strategic resource around the world crude oil is the key commodity for the world economy. Therefore, forecasting crude oil prices has always been considered a very challenging task which drew the interest of researchers. The price of oil is essentially determined by its supply and demand [8]. There appeared to be benefits from disaggregation and for searching for new causal variables. Greater volatility of oil prices could rekindle the integration of petroleum operations designed to save on transaction costs incurred in reducing uncertainty. More sophisticated, and hence more expensive, market instruments might be required to hedge risks. More complex contracts may need to be written among market participants compared with other commodities. Greater price volatility could account for the way the petroleum industry is in the vanguard of developing and applying modern asset valuation techniques [9]. [10] work titled: Applied Analysis Concept Development on Financial Aspect. The Role of asset price, which explained their survey on forecasting output and inflation. Although they mention some historical precedents, their review focused on developments within the past fifteen years. The section concludes with an attempt to draw some general conclusions from their literature.

[11]) in his work titled “Forecasting method in finance”; he reviewed and highlighted some of the key challenges in financial forecasting problems along with opportunities arising from the unique features of financial data. [12] he analyzed the difficulty of establishing predictability in an environment with a low signal-to-noise ratio, persistent predictors, and instability in predictive relations arising from competitive pressures and investors learning. [13] he discussed approaches for forecasting the mean, variance, and probability distribution of asset returns. Finally, He discovered how to evaluate financial forecasts while accounting for the possibility that numerous

forecasting models may have been considered, leading to concerns of data mining. However, research on this study is still ongoing.

3. Methodology

As discussed earlier that two models of ARCH family are considered therefore two methodologies are observed; GARCH and EGARCH. Moreover, the sample data explored are daily data of gold and crude oil from yahoo finance from 2018 to 2023. The actual data are non-stationary but transformed to stationary at first differencing for analysis.

3.1. GARCH Model

The model assumes that forecasts of variance changing in time depends on the lagged variance of capital assets. An unexpected increase or fall in the returns of an asset at time *t*, will generate an increase in the variability expected in the period to come.

$$\sigma_t^2 = \varpi_i + \sum_{j=1}^{q} \beta_j \varepsilon_{t=j}^2 + \sum_{i=1}^{p} \alpha_i \gamma_{t-i}^2 \quad (1)$$

where $i = 0,1,..., p$ is conditional volatility, ϖ_i, α_i and β_j are non-negative constants with $\alpha_i + \beta_j < 1$It should be closer to unity for accuracy, ε_{t-j} is residual and lagged conditional volatility β_j ε_{t-i}^2 are ARCH component and α_i and γ_{t-i}^2 are GARCH component.

3.2. EGARCH Model

Asymmetric relationship in financial time series is called leverage effect which stated that volatility operates in diverse manner depending on the positivity and negativity of volatility that occur. In order to eradicate this asymmetry EGARCH model was developed for optimal forecasting. The model is divided into two parts; mean and variance models:

Mean equation:

$$\mu_t = \gamma_t + \varepsilon_t \quad (2)$$

Variance Equation

$$Log\sigma_t^2 = \alpha + \beta \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} \right| + \omega \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} \right) + \phi \log\left(\sigma_{t-1}^2\right) + \theta\left(z_t\right) \quad (3)$$

where μ_t is the dependent variable (excess return), σ_t is a vector of exogenous variables, ε_{t-1} is an error term, the one step ahead forecast variance σ_t^2 (conditional variance) depends on the mean, $\alpha, \beta, \omega, \phi$ and θ are the coefficients to be estimated and z_t is regressor term.

4. Results and Discussion

In this research, we have studied forecasting method for assets prices. Figures 1 and 2 show volatilities (market fluctuations) of both assets.

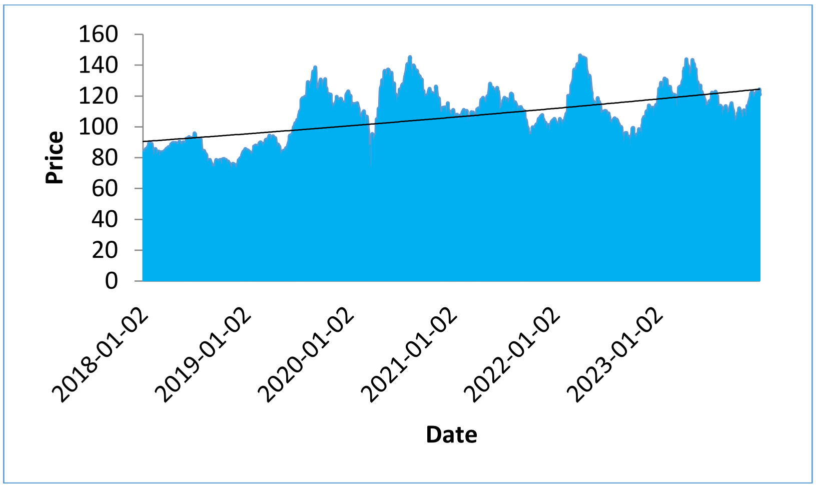

Figure 1: Volatility of Gold

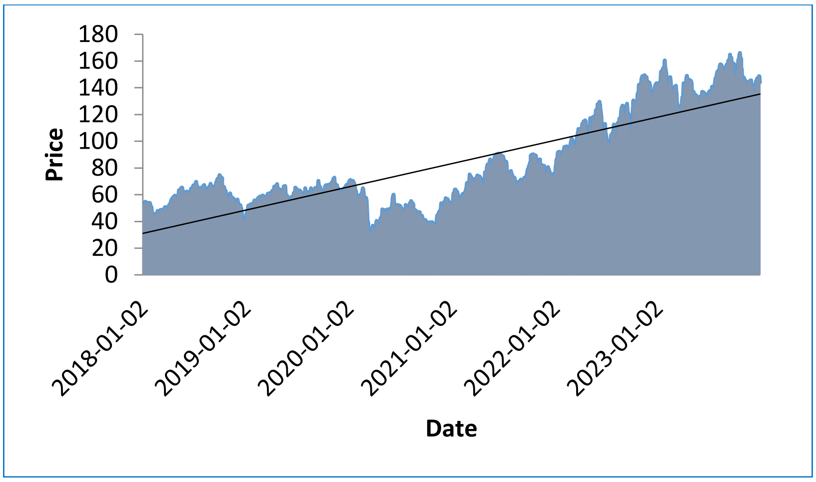

Figure 2: Volatility of Crude oil

Volatility of price means fluctuations of prices in the market; most times investors rely on the volatility of price of assets to forecast future of such assets. Hence, this study focuses on forecasting; therefore, it is imperative to show the volatilities of the two assets in consideration. The trend line in Figures 1 and 2 shows the difference between up and down volatility. The up and down volatility represent the pick and fall period of the asset respectively. In Figure 1 there is a bit pick at the end of 2018 but fall in 2019, at the end of 2019 there is rise in price and 2020 there is high pick but fall at the end of that year. There is a higher pick in 2021, the fluctuation continued till 2022 and higher pick in 2023. In 2024 there is tendency that the price may fall which may still rise in the nearest future.

Figure 2 shows that the price of crude oil had been high from 2018 but fall in 2019 and rise again before the end of that year and continued till 2020, at the end of that year there is a sharp fall in price till 2021 but at the end of that year, it continued rising gradually and in 2022 there is a higher pick, this continued till 2023. This rise was more pronounced in 2023, this continued till 2024 though there may be little fall before the end of 2024 but not significant.

Table 1: Gold

GARCH		EGARCH		
AIC	**SIC**	**AIC**	**SIC**	**Pvalue**
-5.13	-5.12	-5.14	-5.12	0.00

Table 2: Crude oil

GARCH		EGARCH		
AIC	**SIC**	**AIC**	**SIC**	**Pvalue**
-4.34	-4.32	-4.34	-4.36	0.00

The AIC and SIC are statistical tests to evaluate the best forecasting models fit for model selection. Tables 1 and 2 present values of AIC and SIC for the two assets; gold and crude oil, to determine best forecasting model; GARCH and EGARCH models. The guidelines for model selection are, the lower the values of AIC and SIC, the better the model for the asset. Comparing Tables 1 and 2 it is shown that AIC and SIC for EGARCH model is lower than that of GARCH model. Therefore, EGARCH model better forecast both gold and crude oil than GARCH model. Hence, it is observed that the values of AIC and SIC of gold are lower than crude oil. This shows that gold is more reliable than crude oil in the market. This means that gold can serve as hedge and haven than crude oil.

5. Conclusion

As afore mentioned, that the study investigates forecasting methods for assets prices. The research is mostly concerned with optimal model selection for forecasting gold and crude oil. The data for analysis is daily data from yahoo finance that spans through years 2018 to 2023. Figures 1 and 2 show the volatilities (fluctuations) of the two assets prices. It is observed that in recent years the price of crude oil is much higher than that of gold. Moreover, as shown in the figures that the gold has steadier volatility than crude oil, which makes it more reliable. This means, if the volatility of gold is high it would have long high volatility and if it is low, it would be long volatility but in case of crude oil it has sharp high and immediately there is sharp fall.

Table 1 shows that in EGARCH, AIC has value -5.14 and SIC has value -5.12, in GARCH, AIC is -5.13, SIC is -5.12. It is vividly seen that EGARCH AIC has lower value than GARCH while SIC of both models has the same values. Also, Table 2 shows that in EGARCH, AIC with value -4.34 and SIC with value -4.36 and in GARCH, AIC has value -4.34 and SIC with value -4.32. It is observed that AIC of both models has the same values while EGARCH SIC has lower value than GARCH.
In conclusion, both Figures and Tables show that gold has better results than crude oil. According to this research, it is recommended that investors should add gold to their portfolio to serve as hedge and haven during economic recession.

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Appendix

Table A1: Sample of Non-Stationary Data

Date	gold	crude oil
1/2/2018	83.92	47.85
1/3/2018	83.54	49.4
1/4/2018	83.97	50.59
1/5/2018	83.17	52.16
1/8/2018	83.28	52.49
1/9/2018	83.87	52.46
1/10/2018	83.96	53
1/11/2018	84.72	54.72
1/12/2018	85.56	54.54
1/16/2018	85.36	53.54
1/17/2018	86.36	54.02
1/18/2018	85.77	53.84
1/19/2018	87.14	52.61
1/22/2018	87.11	53.47
1/23/2018	88.5	53.62
1/24/2018	89.54	53.88
1/25/2018	87.93	53.59
1/26/2018	88.54	53.69

1/29/2018	87.1	52.31
1/30/2018	88.09	50.52
1/31/2018	89	50.51
2/1/2018	89.01	50.59
2/2/2018	87.24	47.79
2/5/2018	84.84	44.49
2/6/2018	81.97	45.96
2/7/2018	80.69	44.11

Table A2: Sample of Stationary Data

Date	gold	Crude oil
1/2/2018	-0.00453	0.032393
1/3/2018	0.005147	0.024089
1/4/2018	-0.00953	0.031034
1/5/2018	0.001323	0.006327
1/8/2018	0.007085	-0.00057
1/9/2018	0.001073	0.010294
1/10/2018	0.009052	0.032453
1/11/2018	0.009915	-0.00329
1/12/2018	-0.00234	-0.01834
1/16/2018	0.011715	0.008965
1/17/2018	-0.00683	-0.00333
1/18/2018	0.015973	-0.02285
1/19/2018	-0.00034	0.016347
1/22/2018	0.015957	0.002805
1/23/2018	0.011751	0.004849
1/24/2018	-0.01798	-0.00538
1/25/2018	0.006937	0.001866
1/26/2018	-0.01626	-0.0257
1/29/2018	0.011366	-0.03422
1/30/2018	0.01033	-0.0002
1/31/2018	0.000112	0.001584
2/1/2018	-0.01989	-0.05535
2/2/2018	-0.02751	-0.06905
2/5/2018	-0.03383	0.033041
2/6/2018	-0.01562	-0.04025
2/7/2018	0.017846	-0.02516