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Modelling and Forecasting Gold Price Return and Its Volatility

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ABSTRACT

In the financial industry, forecasting gold price return and its volatility are crucial. Even tiny improvements in prediction performance can add up to a significant sum of money. One strategy for anticipating gold price volatility is the GARCH family of models. The GARCH process provides a more realistic background for estimating financial instrument values and rates than other models. The aim of this research is to model the volatility and price of gold via GARCH(1,1), EGARCH(1,1) and TGARCH(1,1) models. The data was employed from 4th January 2016 until 29th October 2021 retrieved from Yahoo Finance website. The data was converted into return price to make it stationary. The performance of the estimated models was compared by using information criterion. The best model is the one that has the lowest values of information criterion. TGARCH(1,1) is outperformed other proposed models where it has an ability to capture the bad and good news that exist in the data series. The best model is used to forecast the volatility and return of gold price. The return is expected to be constant with high risk for the next 5 days from the point origin in this study.

Keywords: *GARCH, gold price, price return, volatility, forecasting*.

1 INTRODUCTION

Gold has become a precious asset, which has managed to attract many investors, and the demand has increased over time. Gold plays an important role as it can help stabilizing influence for investment portfolios [1]. Variety of factors could determine the price of gold, the common factors are people's opinions of its value, global economic events, the amount of gold bought and sold, and other external influences such as new discoveries, significant acquisitions, and so on. Consequently, with the rising demand for gold in Malaysia and around the world, it is important to develop a model that could reflect the pattern of the gold market and forecast the movement of gold prices [2]. As a result, the modelling and forecasting of gold price volatility is essential.

Volatility modelling and forecasting have played a great role, especially in financial markets, for many years. Forecasting uses historical data to predict the direction of future trends for an upcoming period, such as assigning a budget or plan. The financial markets also use volatility estimates as a basic risk indicator, and volatility appears in option pricing formulas derived from those models. Reliable volatility estimates and projections are critical for risk mitigation and portfolio management

[3]. Over the years, a variety of stylized statistics about the fluctuations of financial asset prices have arisen.

Gold future market data was used in modelling the price and volatility in this study. Gold investment has attracted a lot of attention as the assumption is that gold can be treated as a store of value, and it is not affected by inflation. As the risk in the stock and bond markets increased, investors were particularly interested in increasing their positions in gold. This interest has prompted this research focused on gold investment. To capture the gold price and its volatility, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models were applied. Furthermore, there are several cases or extreme events that could result in large changes in gold prices and cause the asymmetry of price returns [4] . Hence, a performed volatility model must be able to forecast volatility, and these facts must be captured by a good volatility model. There are many volatility models that are used in forecasting the pattern of data.

GARCH models were developed, specializing in financial time series. These models also have properties like heavy tails, volatility clustering, and independent serial correlation that are not likely happened in traditional linear time series models. In addition, financial instrument volatility is rarely constant and typically varies over time. Volatility clustering was captured by the GARCH model, which uses volatility as a drift process [5]. Volatility clustering occurs when large price movements on one day are followed by large movements on subsequent days, which leads to the formation of temporal clusters.

There are many research on modelling the gold price that employ the same methods. However, this research used the daily data from 2016 to 2021 where the situation might be different due to many factors. Therefore, the objectives of this study are to model the volatility and the return of gold price, to access the performance of the models, and to forecast the gold price return and risk in the future for 5 consecutive days.

2 LITERATURE REVIEW

2.1 General Autoregressive Conditionally Heteroskedasticity (GARCH) Model

GARCH is the most common method for forecasting high volatility data. The GARCH model is a model of conditional variance that changes over time. Bollerslev [6] stated that the GARCH model is an expansion of Engle's ARCH model from 1982. GARCH is a methodology for explaining future deviations that considers prior variations [7]. Ping et al. [8]studied the gold price of Kijang Emas and found that the GARCH model is the most appropriate model with the lowest value of AIC.

Jain and Biswal [9] also applied the GARCH model to estimate the time-varying correlation. Even though the value of AIC among the models is approximately the same, they chose GARCH because it is the simplest model among the other GARCH family models. GARCH is the highest order in the ARCH model and was selected to determine the dynamic of the conditional variance. According to [5], the simple linear GARCH model predicts with greater accuracy than other non-linear models such as APARCH, TARCH, and FIGARCH. Even though, GARCH is the simplest model among them, it still has its weaknesses. GARCH only good in forecasting a symmetric characteristic of volatility but not asymmetric. To deal with the volatility's asymmetric properties, many extensions of asymmetric GARCH type models have been developed for example, TGARCH, EGARCH, APARCH, and many others.

2.2 Exponential General Auto Regressive Conditionally Heteroscedasticity (EGARCH) Model

EGARCH is one of the members of the GARCH family. It was developed by [10] where the model has an ability to capture the effect of asymmetric variance. It has some unique properties that make it helpful in the context of asset pricing. The main structure for the mean and variance is almost similar to the typical GARCH model. This main different from the GARCH variance structure is the log of the variance. The EGARCH model is applicable for time series data that exhibit long-term memory and leverage effects on volatility during both periods. Research has revealed that higher volatility during the revolutionary period for all indices was affect the higher standard deviations for both daily returns and absolute returns. During the revolutionary period, the leverage effect was increasingly significantly. However, during the pre-revolution period, a long memory was more evident [11].

A logarithmic function is used in the EGARCH model to tackle asymmetric effects [5]. This model also captures asymmetric reactions to shocks in the time-varying variance while ensuring that the variance is always positive. A negative shock in economic study and financial markets usually means bad news, resulting in a more uncertain future [7].

EGARCH has the smallest error compared to APARCH and TGARCH, which makes it the most appropriate model compared to TGARCH and APARCH in modelling the data [12]. Besides, EGARCH model is written in a form of logarithmic, implying that parameters are not restricted, allowing them to have negative values and at the same time maintaining a non-negative conditional variance [13]. The EGARCH model can explain the common leverage effects observed in financial times.

2.3 General Auto Regressive Conditionally Threshold Heteroskedasticity (TGARCH) Model

TGARCH was first introduced by [14] where the conditional standard deviation was modified by employing a piecewise linear function of past values of the white noise. TGARCH is a model that can better performed in most financial data than the GARCH model since it able to react differently on the volatility for different signs of the lagged residuals.

Sabiruzzaman et al. [15] investigates the performance of GARCH versus TGARCH model in forecasting volume trading index and concludes that TGARCH model is perform better than GARCH model. This is mainly crucial when one is dealing with the situation of asymmetric information that captures the leverage effect of the volatile stock market.

Lim and Sek [16] also found TGARCH model performed better during the crisis period in describing the stock market volatility in Malaysia. Similar research for example [17], [18] stated that TGARCH outperformed symmetric GARCH model for financial data series. Hence, TGARCH model is expected to fit well on gold price data due to its ability to detect effect of bad and good news.

The findings of the previous study show that in different time frames, symmetric and asymmetric GARCH models perform differently. Previous research, however, has revealed that there is no consent on the optimum model for capturing volatility. Some research suggested that basic GARCH models provide superior outcomes, while others demonstrate that other GARCH models work better. These model's performance varies depending on the market and time. Hence, this research attempt to forecast the gold price and volatility using GARCH, EGARCH and TGARCH models.

3 METHODOLOGY

3.1 Source of Data

In this study, the data was collected from January 2016 until October 2021 in daily form retrieved from Yahoo! Finance website. Essentially, the variable under this research is the gold prices suitable for the research objective, which is modelling and forecasting the gold price and its volatility. In this research, the data was converted into price return due to non-stationary condition. Let Y_t be the gold price at the current time of t and Y_{t-1} is the gold price at one period behind. Hence, the price return, R_t can be defined as the difference of gold price between the current dan one period behind, $Y_t - Y_{t-1}$.

3.2 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

The expected return is kept constant in a GARCH model since volatility or variance is determined by previous volatility or variance. The price return can be described as follows:

$$R_t = \mu + \varepsilon_t \tag{1}$$

where ε_t is the residuals and assumed to be normally distributed with zero mean and non-constant variance, σ_t^2 , $\varepsilon_t \sim N(0, \sigma_t^2)$.

The conditional variance of GARCH(1,1) is given as, [6]:

$$\sigma_t^2 = \omega + (\alpha_1 \varepsilon_{t-1}^2) + \left(\beta_1 \sigma_{t_{t-1}^2}\right) \tag{2}$$

where $\alpha_1 + \beta_1 < 1$. The summation of $\alpha + \beta$ should be less than 1 but approaching to unity and $\beta > \alpha$.

3.3 Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) model

The Exponential GARCH model, indicated as EGARCH (1,1), includes the asymmetric influence of positive and negative sudden changes on volatility, with the latter producing higher levels of volatility, although they have the same magnitude. The volatility of an EGARCH (1,1) can be stated as follows in general, [10]:

$$\ln(\sigma_t^2) = \omega + \alpha \left[\left|\varepsilon_{t-1\sqrt{\sigma_{t-1}^2}}\right|\right] + \beta \ \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \tag{3}$$

where σ^2 is the conditional variance since it is a one period ahead estimate for the variance calculate on any past information thought relevant.

However, β is the persistence parameter, α and γ denote the size and leverage effect parameters, respectively. It is expected that the leverage effect is exponential and the forecasts of the conditional variance are certain to be non-negative.

3.4 Threshold Autoregressive Conditional Heteroscedasticity (TGARCH) Model

The TGARCH model assumes that unexpected changes in the price returns or there is different effect on the volatility of the price return. A TGARCH (1,1) model can be expressed as follows, [14]:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \delta D_t \varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{4}$$

where $D_{t-1}$is an indicator for negative ε_{t-i}. Meanwhile, α, δ and β non-negative parameters that satisfy the same requirements as GARCH models.

From the Equation (4), it can be perceived that a positive ε_{t-1} changed $\alpha_i \varepsilon_{t-i}^2$ to σ_t^2, and a negative ε_{t-i} affects the $(\alpha_i + \delta_i)\varepsilon_{t-i}^2$ with $\gamma_i > 0$. The aforementioned alternative models are better than the GARCH models in describing some stylized occurrences. For some cases, to isolate the effects of previous shocks, the model uses a threshold of zero.

3.5 Model Estimation

The Maximum Likelihood (ML) approach is used to estimate the parameters of the GARCH model, using varying distributional assumptions for the error components. The maximum likelihood estimation can be written as:

$$(\theta) = f(X_1, X_2, \dots, X_n; \theta) \tag{5}$$

$$L(\theta) = \prod_{i-1}^{n} f(X_i)\,;\theta \tag{6}$$

The function $L(\theta)$ is maximized by taking the logarithm of likelihood function. The parameter can be obtained through the first derivative of the log likelihood function equal to zero.

3.6 Diagnostic Checking

3.6.1 Ljung-Box Test

The Ljung-Box test examines whether the errors are independent and identically distributed or whether the residual autocorrelation is non-zero. To perform the Ljung Box test, the statistic Q is as follows:

$$Q(m) = n(n+2)\sum_{j=1}^{m} \frac{r_j^2}{n-j} \tag{7}$$

where
r_j^2 = the accumulated sample autocorrelations
m = the time lag
n = number pf observations

The null hypothesis should be rejected and conclude that the model is unfit.

$$Q > \chi^2_{1-\alpha,h} \tag{8}$$

where
$\chi^2_{1-\alpha,h}$= the value found on the chi-square distribution table for significance level of α and h degrees of freedom

3.7 Performance Measures

This paper employs three common tools in measuring the model's performance namely as Akaike Information Criterion, Bayesian Information Criterion and Hannan-Quinn Information Criterion. The best model is the model that yields the lowest values obtained from these three criteria mentioned.

3.7.1 Akaike Information Criterion (AIC)

AIC measure the goodness of fit of a statistical model by evaluating a model from a set of models that has been estimated. The formula is as follows:

$$AIC = -2\ln L + 2k \tag{9}$$

where L is the maximized value of the likelihood function for the estimated model and k is the number of free and independent parameters in the model. The model with the lowest AIC value is the best fit model.

3.7.2 Bayesian Information Criterion (BIC)

BIC is a criterion for model selection among a finite set of models same as AIC. The formula of BIC is as follows:

$$BIC = -2\ln(L) + k\ln(T) \tag{10}$$

where L is the maximized value of the likelihood function while k is the number of parameters in the model.

3.7.3 Hannan-Quinn Information Criteria (HQIC)

Hannan-Quinn Information (HQIC) is another option of performance measure instead of Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Additionally, the HQIC can be used to compare estimated models only when the numerical values of the dependent variable are identical for all the estimates being compared. The formula is given as follows:

$$HQIC = -2\ln(L) + k\ln(\ln(n)) \tag{11}$$

where L is the log-likelihood, k is the number of parameters and n is the number of observations.

4 RESULTS AND DISCUSSIONS

4.1 Description Of Return of Gold Price

Figure 1 shows the gold price from January 2016 until October 2021. The price was moving up and down steadily until end of 2018. At the beginning of 2019, the price started to hike significantly, and the peak exceeded USD2000 by the mid 2020. The data series become more volatile as the price start the momentum at early year of 2019 and makes the forecasting process become more challenging. The increasing trend might suggest the price might not be stationary. The high volatility along the period may contribute also to instability in variance and lead to high risk.

Figure 1: The Gold Price from January 2016 until October 2021

Table 1: Description of Gold Price

n	Mean	Median	Skewness	Kurtosis	Standard error
1465	1447.09	1321.1	0.72	-0.99	6.47

Table 1 shows the descriptive statistics of gold price. The mean value for the gold price is USD1447.09 (n=1465), while the median is USD1321.1. The skewness and kurtosis value are 0.72 and -0.99 respectively which approaching to zero indicates that the gold price data is a normal distribution. Since the gold price is suspected to be not stationary, Augmented Dickey-Fuller Test was performed to confirm the stationarity of the data. The result of stationary between the gold price and return is as shown in Table 2.

Table 2: Results of ADF test for gold price vs return

	Gold price	Return
Dickey-Fuller	-1.8328	-10.838
P-value	0.6491	0.01
Conclusion	Not stationary	Stationary

The p-value as depicted in Table 2 for gold price is more than 0.05. Hence, the gold price is not stationary data. However, the p-value for the return is less than 0.05. Therefore, the return price is stationary.

Since the gold price is not stationary, the first order of differencing was performed. The first order of differencing is where the current price, y_t minus with the price of one period before, y_{t-1}. In investment, data of the first order of differencing is called "return". Figure 2 shows the return of gold price from the year of 2016 to 2021. The chart reveals that the return data after differencing is stationary with the values volatile around zero.

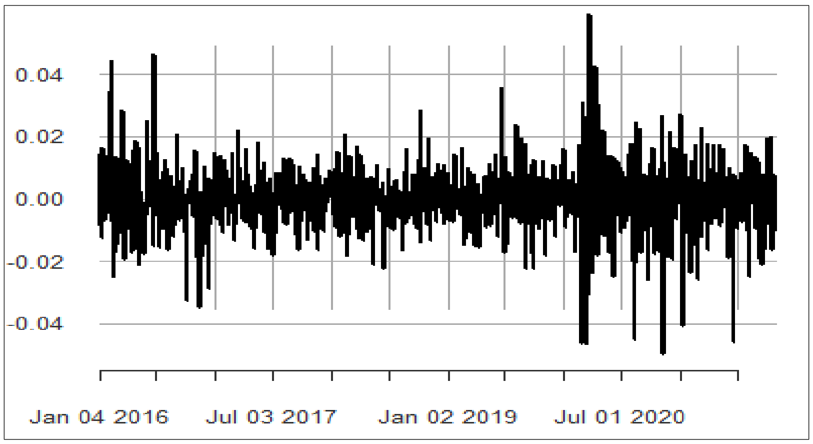

Figure 2: The Gold Price Return from January 2016 until October 2021

Table 3: Description of Gold Price Return

n	Mean	Median	Skewness	Kurtosis	Standard error
1464	0	0	-0.01	5.72	0

Table 3 shows the mean and median for the return gold price is USD0 which mean on the average the gold price is neither gain profit nor loss. The distribution is approximately symmetric since the skewness is -0.01, and the kurtosis is 5.72, indicating that its tails are longer and fatter, and its central peak is usually high and sharp. High kurtosis of the return distribution indicates the investor will encounter occasional extreme returns (either positive or negative), more extreme than the usual + or - three standard deviations from the mean that is predicted by the normal distribution of returns.

4.2 Modelling Gold Price Return via GARCH(1,1), EGARCH(1,1) AND TGARCH(1,1) Models

4.2.1 Parameter Estimation

Table 4 shows that the parameters are estimated by assuming that the errors are normally distributed. The first model to be estimated is the GARCH(1,1) model. Based on Table 3.4, the GARCH(1,1) model shows that the model has 4 parameters which are μ, ω, α and β. The p-values for parameters μ and ω are more than 0.05 which means that they are not statistically significant. It is the opposite for parameters α and β. They are statistically significant since the p-value not more than 0.05.

For EGARCH(1,1) model, the results from Table 4.4 indicates that the coefficient of α parameter were positive and significant which reflects the shock effects. It means that the gold return's volatility was affected by the shocks. In addition, the coefficients of the β parameters indicate the volatility persistence was positive. The leverage effect which indicates by γ shows that there is there is positive and significant relationship between gold price returns and conditional volatility. Moreover, a positive value on the asymmetric term implies that positive news have greater impact on volatility more than negative news with the same magnitude.

Last but not least, the TGARCH(1,1) model shows that α and β terms are significant, with the p-value of 0.0002 and 0.0000 respectively. Both p-values are less than 0.05 which indicates that they are significant. However, it is the opposite for μ, ω and γ with the p-value exceed 0.05. Other than that, the results also show that the coefficient for γ is negative for the TGARCH(1,1) model, implying that good news have larger impact than bad news.

Table 4: Estimated Parameter of GARCH(1,1), EGARCH(1,1) and TGARCH(1,1)

Model	Coefficient	Estimate	Standard error	T-value	P-value
GARCH(1,1)	μ	0.000237	0.000217	1.0927	0.2745
	ω	0.000001	0.000001	1.0355	0.3004
	α	0.026917	0.004925	5.4649	0.0000
	β	0.964370	0.005056	190.7298	0.0000
EGARCH(1,1)	μ	0.000290	0.000181	1.6063	0.1082
	ω	-0.116283	0.001832	-63.4730	0.0000
	α	0.030815	0.009131	3.3749	0.0007
	β	0.986998	0.000194	5092.3950	0.0000
	γ	0.088152	0.005291	16.6617	0.0000
TGARCH(1,1)	μ	0.000305	0.000218	1.3992	0.1617
	ω	0.000001	0.000001	1.3184	0.1873
	α	0.053158	0.014434	3.6828	0.0002
	β	0.948676	0.008893	106.6742	0.0000
	γ	-0.031575	0.015480	-2.0397	0.0413

4.2.2 Diagnostic Checking

In this section, the Weighted Ljung-Box Test on Standardized Residuals is used to test whether the error terms for GARCH(1,1), EGARCH(1,1) and TGARCH(1,1) models has a serial correlation or not.

Table 5: Weighted Ljung-Box Test on Standardized Squared Residuals

Model	Group	Statistics	P-value
GARCH(1,1)	Lag[1]	0.7398	0.3897
	Lag[2*(p+q)+(p+q)-1][2]	4.0929	0.2427
	Lag[4*(p+q)+(p+q)-1][5]	5.2845	0.3888
EGARCH(1,1)	Lag[1]	0.2458	0.6200
	Lag[2*(p+q)+(p+q)-1][5]	2.0155	0.6148
	Lag[4*(p+q)+(p+q)-1][9]	3.5124	0.6722
TGARCH(1,1)	Lag[1]	1.1340	0.2869
	Lag[2*(p+q)+(p+q)-1][2]	2.9540	0.4155
	Lag[4*(p+q)+(p+q)-1][5]	3.8160	0.6201

Table 5 shows the Ljung Box Test on standardized squared residuals for GARCH(1,1), EGARCH(1,1) and TGARCH(1,1) respectively. For GARCH(1,1), since the p-value is greater than 0.05, failed to reject null hypothesis. Therefore, there is no evidence of serial correlation on standardized squared residuals. Hence, the residuals are behaved like white noise process, which means that the GARCH(1,1) model is valid for modeling gold price return.

Furthermore, the p-value of EGARCH(1,1) and TGARCH(1,1) model was also higher than 0.05 indicates that the residual of the models are independent and identically distributed. Thus, failed to reject the null hypothesis and conclude that there is no autocorrelation problem on standardized squared residual.

4.2.3 Performance of GARCH(1,1), EGARCH(1,1) and TGARCH(1,1) Models on Return of Gold Price

The performance of the GARCH type models varies substantially depending on the considered information criterion. The result in Table 4.6 contains model selection criteria for the three models based on their fitness and performance with respect to the basic three common selection criteria, which are the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Hannan-Quinn Information Criteria (HQIC).

Table 6: Performance of GARCH Models on Return of Gold Price

	GARCH(1,1)	EGARHC(1,1)	TGARCH(1,1)
AIC	-6.6362	-6.6377	-6.6387
BIC	-6.6218	-6.6197	-6.6206
HQIC	-6.6309	-6.6310	-6.6319
Ranking	3	2	1

From Table 6, GARCH (1,1) model does not perform very well and is ranked at the bottom rank of all the tested models. However, based on BIC, GARCH(1,1) outperforms compared to other models. Meanwhile, the EGARCH (1,1) model performs better, which is ranked second lowest based on Akaike and Hannan-Quinn information criterion values. Moreover, the TGARCH (1,1) model is the most outperformed model compared to GARCH (1,1) and EGARCH (1,1) models. Based on AIC and HQIC values, the TGARCH model exhibits the lowest value, which indicates that it is the best fit model.

Interestingly, the results obtained were supported by [8] who studied Malaysian gold using symmetric and asymmetric GARCH models. In the study, it was found that the TGARCH (1,1) model is the best fit for all the series as decision making criterion, Akaike information criterion (AIC) and Hannan-Quinn information criterion (HQIC) are least in this model. Overall, the TGARCH (1,1) model provided the best performance measures among the tested model, indicating the most appropriate model for forecasting the future gold price.

4.2.4 Forecasting Using Best Model

The prediction was executed by using the TGARCH(1,1) model, since it is the best model among the three models.

Table 7: Forecast Value for The Return of Gold Price and its Volatility

Time	Price Return	Volatility
t+1	0.000305	0.008383
t+2	0.000305	0.008397
t+3	0.000305	0.008410
t+4	0.000305	0.008424
t+5	0.000305	0.008437

Table 7 indicates that the forecast of gold price return for 5 days ahead is more than 0. It means that there is a low positive return for the gold price based on the predicted values by using TGARCH(1,1) model. The predicted volatility is expected to be increasing indicates that it can potentially be scattered out above the range if its volatility increases over the time. This also means that the return of gold price can move drastically in positive or negative direction in a short period of time.

5 CONCLUSION

The main objective of this research is to model the gold price data and its volatility. Since the gold price is not stationary, the gold price was converted into return by performing first order of differencing. The models are GARCH(1,1), EGARCH(1,1), and TGARCH(1,1). These models are capable of capturing volatility clustering or fluctuation periods and forecasting future volatility. EGARCH(1,1) and TGARCH(1,1) were found to be able to capture the news impact in the market.

In order to determine the most suitable model to forecast the future gold price, AIC, BIC and HQIC were used to measure the performance of GARCH type models. The model with the lowest AIC, BIC and HQIC values is the better fit model. TGARCH(1,1) model fits the series well and outperforms the other models. The superiority of the TGARCH(1,1) model for modelling the series is highlighted by the lowest AIC and HQIC values compared to the corresponding GARCH(1,1) and EGARCH(1,1) models. Therefore, the TGARCH(1,1) model is the most potential approach among the tested models in modeling and forecasting future gold prices.

In this study, forecasting gold price return were analyzed. The returns were forecasted for 5 days ahead. As the results, the gold price return is not giving much profit or return to the investors for certain period.

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