Turkish Economic Review
www.kspjournals.org
Volume 6 September 2019 Issue 3

Forecasting volatility of gold: Comparison of Turkish gold and equity markets' risk profile

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Abstract. Predicting price changes of a commodity thus, forecasting volatility thereof have significant importance for the risk measurement purpose. Perception is that the highly volatile assets overreact more under stressed market conditions, cause excessive volatility and are traded with a discount. In this paper, we evaluated volatility structure of gold and equity markets in Turkey with GARCH volatility modeling methodology, an extended version of ARCH model. Comparison of volatility clustering and overall risk profile of both markets was made. The results show that persistence exists in the volatility process and current conditional volatility of gold prices is significantly impacted by its own past shocks and volatility. The results also confirms the volatility clustering that high volatilities are likely to be pursued by high ones and vice versa in both gold and equity markets. Parallel to literature finding, gold is a diversification instrument because of its low correlation with stock markets and its low risk profile feature induced with low volatilities in gold markets than equity markets.
Keywords. Gold, Equity, Volatility, Risk.
JEL. G10, G11, G15.

1. Introduction

Volatility forecasting is one of the most important concept in the financial markets not only for portfolio composition and asset management purpose but also as a measure of risk. Definition of volatility in the Investopedia is *"a statistical measure of the dispersion of returns for a given security or market index. Volatility can either be measured by using the standard deviation or variance between returns from that same security or market index. Commonly, the higher the volatility, the riskier the security."*

In order to model and analyze volatility, the ARCH model (autoregressive conditionally heteroscedastic) has a widespread preference in finance. It is developed by Engle (1982) in order to describe behavior of changing variance over time. He brought this concept against the econometric literature that assumes a constant one-period forecast

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variance. Afterwards, the Generalized ARCH (GARCH) which addressed the limitations of the ARCH model was developed by Bollerslev (1986) and Taylor (1986), independently. Akgiray (1989) and West & Cho (1995) find the GARCH model superior to ARCH, exponentially weighted moving average and historical mean models for forecasting volatility.

Based on various studies' outcomes, gold price tends to rise with bad news and gold is assumed as a safe haven and mean of eliminating financial risks (Reboredo, 2013; Ibrahim, 2012; and Tully & Lucey, 2007). In this regard, we evaluated risk profile of gold and equity markets in Turkey with GARCH volatility modeling methodology in this paper. Subsequently, after the literature review, the data set and the methodology applied were explained in brief. Consequently, we evaluated the findings from the empirical analysisand concluded with observations on volatility clusteringand risk profile of the gold and equity markets.

2. Literature review

In last decade, safe haven feature of the gold and whether gold is a mean for avoiding financial risk are questioned. Reboredo (2013), Ibrahim (2012) and Tully & Lucey (2007) studies' results confirmed that gold is a risk-free investment vehicle and a hedging instrument against risk (Ghosh *et al.*, 2004). Baur & Lucey have (2010) also addressed hedging and safe haven features of gold via utilizing GARCH and found evidence that gold is a safe haven against stock in times of market turmoil.

Parallel to most literature findings on negative correlation in between equity and gold markets, İbicioğlu (2012) study which utilized multidimensional scaling method also confirmed Turkish securities and gold yields differ. İbrahim (2012) evaluated whether there was a relationship between capital markets and gold in the Malaysian economy via TGARCH/EGARCH modeling and reached to a conclusion that there is a positive but limited correlation between gold and capital markets. Another study on Turkish stock and gold market interaction via utilizing the Johansen cointegration and Granger causality tests found a high correlation between the values of gold and other assets and a long-term significant relationship before and after the 2008 global financial crisis (Doğru & Uysal, 2014). However, the safe haven effect of gold become oblique by the US dollar as a safe haven currency during the Global Financial Crisis (Baur & McDermott, 2016). Nagayev & Dincer's (2018) study also confirms that gold is a safe haven in difficult market periods in Turkey.

Changes in volatility are significantly important in taking investment decisions. While Wennström (2014) analyzed volatility forecasting performance of GARCH family on Nordic equity markets, Du (2012) also modeled volatility of gold price with other precious metals prices by GARCH models. Regarding volatility behavior analysis of gold and other markets or instruments; Akgiray (1989), West & Cho (1995), Brooks (2014), Wennström (2014) and Costa (2017) find the GARCH model outperforms

ARCH.Likewise, Ping *et al.*, (2013) studied forecasting gold price in Malasian market via GARCH Model. Their study concludes that GARCH is a more appropriate model.

Sinha & Mathur (2016) studied gold and equity markets in India and observed strong volatility spillover from spot to futures markets which is an significant implications for financial market players, e.g. investors and asset managers, for their trading and hedging strategies.

Literature is also rich on the causality relationship of gold with stock markets (e.g. Smith, 2001; Mishra, Das & Mishra 2010, Chiang, Lin & Huang, 2013). Global financial crisis also put gold into limelight as alternative investment instruments, in addition to equity and debt securities due to gold's safe hedge perception in the market. Other studies in this area found significant impact of equity market on gold market (Koutsoyiannis, 1983; Topcu, 2010; Özkan & Kolay, 2016). However, Ibrahim (2010) found a significant positive but low correlation between gold and once-lagged stock returns and potential benefits of gold investment during periods of stock market falls (Ibrahim, 2010).

Smith (2001) and Ghosh *et al.*, (2002) observed long run relationship of gold and equity while Sandal *et al.*, (2017) found no such relationship. According to Akel & Gazel's (2015) findings, gold is a diversification instrument because of its low correlation between stock and gold.

3. Data and methodology

Our data set consist of Gold (USD/Ons) and Borsa Istanbul equity index (BIST 100) series from Bloomberg data vender. BIST 100 series is converted into USD via USD/TRY FX rate acquired from Central Bank of Turkey electronic data distribution system (https://evds2.tcmb.gov.tr/). Each series consists of 4610 daily observations for the period of January 3, 2000 to May 31, 2018. Series were converted to return series before including into analysis.

Before starting to the analysis, we test the data for stationarity in order to determine if a stochastic trend is existing. Among various tests for the stationarity (unit root), we preferred commonly used Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The Test's null hypothesis (H_0) is that time series have a unit root and series is stationary if H_0 is not accepted. Test results for 4609 observations are given in the table below and results confirm stationarity feature of the series:

Table 1. *ADF and PP Tests' Results*

	ADF Test	PP Test	1% Critical Val.	5% Critical Val.	10% Critical Val.
XAU/USD	-61.533	-69.647	-3.430	-2.860	-2.570
BIST100	-65.072	-65.038			
USD/TRY	-63.554	-63.418			

Note: MacKinnon approximate p-value for Z(t) = 0.0000

In order to describe behavior of the variances of variables' change over time, we will use the Bollerslev (1986) and Taylor's (1986) GARCH model, an extension of Engle's (1982) ARCH processes. The conditional heteroscedastic model with (p,q) order is as follows in the below equationwhere $\omega > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, and the innovation sequence $\{\varepsilon_i\}_{i=-\infty}^{\infty}$ is independent and identically distributed with $E(\varepsilon_0) = 0$ and $E(\varepsilon_0^2) = 1$ (Fryzlewicz, 2007):

$$y_k = \sigma_k \varepsilon_k \tag{1}$$

$$\sigma_k^2 = \omega + \sum_{i=1}^{p} \alpha_i y_{k-i}^2 + \sum_{j-1}^{q} \beta_j \sigma_{k-j}^2,$$

Here, the assumption is that, the conditional variance of y_k has an autoregressive (AR) structure and has a positive correlation with its recent past and recent values of squared returns.Accordingly, a volatility clustering is observed where large values are likely to be pursued by large values and vice versa.

Various empirical analysis accepted that GARCH (1,1) model provides a good fit for the time series (Bollersley, 1986; Colm & Patton, 2000; Wand & Wang, 2001). Before estimating GARCH (1,1) model, we apply Langrange Multiplier (LM) test to observe whether ARCH effect is present. The ARCH-LM test is a methodology to test for the lag length of ARCH errors using the Lagrange multiplier test which was proposed by Engle (1982). This test should be done before applying the GARCH models to the data. If the p-values for this test are all very small, then the null hypothesis, say the dataset has no ARCH effects should be rejected. Based on this test, it is secured and proper that we can fit this data to a GARCH model. Under the condition that ARCH effect is existing, it is appropriate to match the volatility with the GARCH model (Chiang, Lin & Huang, 2013).

4. Descriptive analysis

Volatility is a very important indicator in financial market therefore, there are some important benchmarks followed widely by market participants. One of them is the VIX volatility index calculated by the Chicago Board Options Exchange (CBOE). It is also known as fear indexwhere an index level above 30 is assumed as presenting a stressed market. VIX represents market expectation of 30-day forward-looking volatility derived from the price of the S&P 500 index options (CBOE).

The CBOE also calculates the Gold ETF Volatility Index ("Gold VIX": GVZ) which measures the market's expectation of 30-day volatility of gold prices of options on SPDR Gold Shares. As can be observed, most of the time in 2008-2017 period, VIX and GVZ are highly correlated (87%). Most investors instinctively know that gold tends to rise when bad news hits the economy. Gold is also assumed as the fear trade.

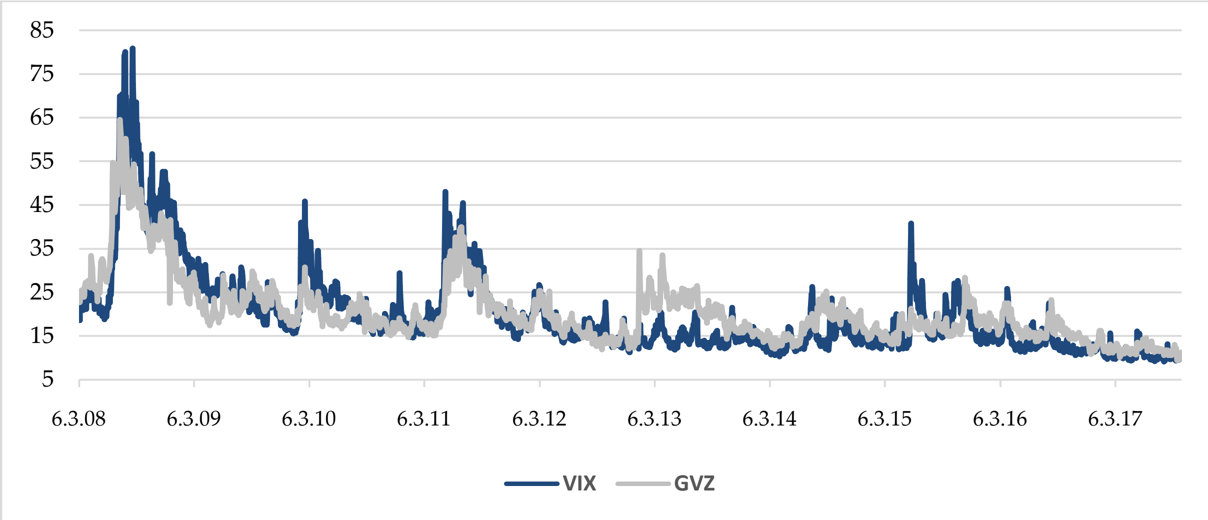

Figure 1. *Volatility Indices of Gold and Stock Markets*
Source: [Retrieved from]. Accessed on 23.11.2018.

Mean of both VIX and GVZ is 20 for the June 2008 - December 2017 period and VIX has a higher volatility then GVZ with a standard deviation of 10.13 and 7.74 respectively. As aforementioned, index level above 30 represents a stressed market and below 20 is assumed asa quiet market.

Table 2. *Descriptive Statistics of the Volatility Indices of Gold and Stock for 2008:06-2017:12*

	Mean	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
VIX	19.93	16.79	10.13	6.72	2.31	9.14	80.86
GVZ	20.42	18.52	7.74	5.73	2.09	9.43	64.53

Our analysis is based on the market data from Borsa Istanbul gold spot market prices and Borsa İstanbul Equity Market broad based equity index which includes 100 stocks. From the graph illustrated below, a volatile trend is observed for the equity market compared to others. Gold prices tracked a steady uptrend until 2011-end and then, pursued a down-trend. USD/TRY price series followed a stable uptrend.

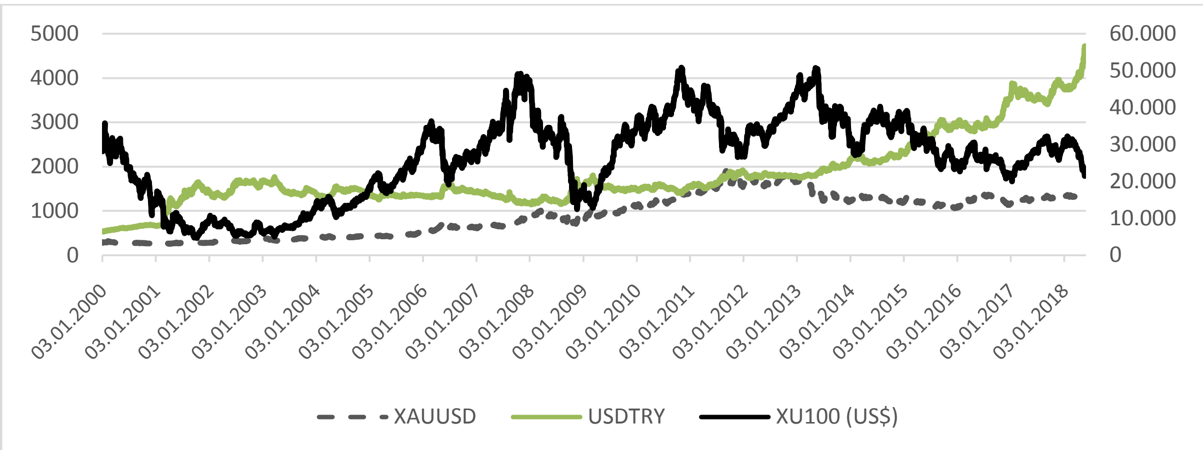

Figure 2. *Borsa Istanbul Gold and Equity Market Return Series (2000:01- 2018:05)**
Note: For the graphical display purpose, FX rate is multiplied with 1000

Descriptive statistics of our data set in the analysis is depicted in the table and graph below. The data set covers 2000:01- 2018:05 period with consists of 4610 daily observations. In return series the mean of each is very close to zero, as well as the median and a not very large standard deviation. Each of them has excess kurtosis.

Table 3. *Descriptive Statistics of Gold, Equity Index and USD/TRY FX rate (2000:01-2018:05)*

	Return series			Price series		
	XAUUSD	XU100 (US$)	USDTRY	XAUUSD	XU100 (US$)	USDTRY
Mean	0,03	0,03	0,05	902,91	26.366,48	1,82
Median	0,04	0,06	0,00	935,49	28.087,26	1,55
Std. Dev.	1,12	2,69	1,16	466,83	11.299,87	0,78
Kurtosis	8,75	10,49	415,21	-1,35	-0,8	1,1
Skewness	-0,04	0,10	11,58	0,06	-0,24	1,25
Minimum	-7,50	-23,16	-7,07	255,65	4.643,36	0,54
Maximum	8,71	22,17	43,00	1.900,31	50.828,24	4,72

In the gold (XAUUSD) return series; the excess kurtosis (8.75) suggests that series have heavy (fat) tails relative to normal distribution and the negative skewness (-0.04) shows that the series are left skewed indicating that negative returns dominate positive returns in general. Likewise, in the BIST Equity Market XU100 index return series we observe an excess kurtosis (10.49) which suggests that series have fat tails relative to normal distribution and the skewness of 0.10 shows that the series are right skewed demonstrating that positive returns dominate negative returns in general. Similarly, the excess kurtosis in the USDTRY return series suggests a fat tails and the series are right skewed representing that positive returns dominate negative returns in general.

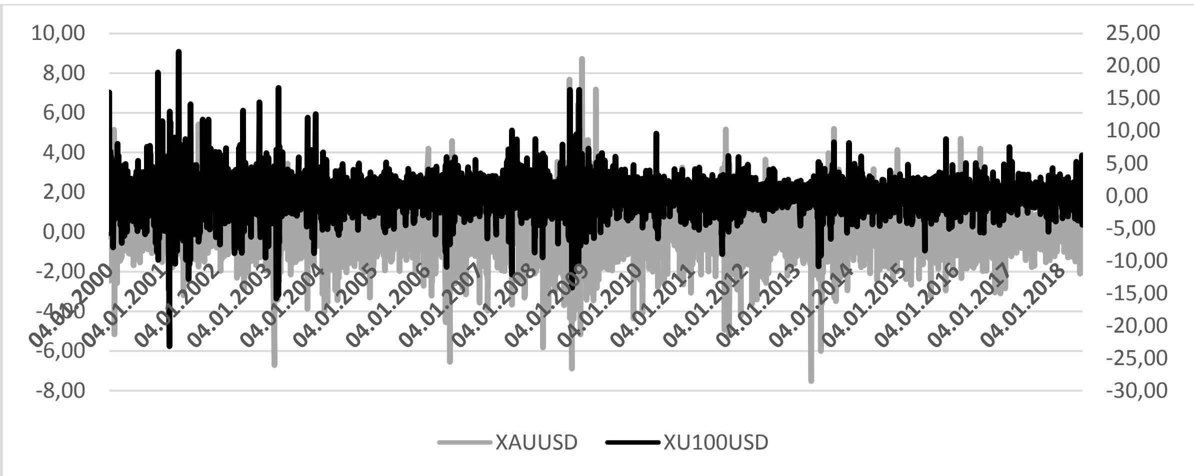

Figure 3. *Borsa Istanbul Gold and Equity Market Return Series (2000:01- 2018:05)*

When we evaluated the correlation matrix of the data set given below; gold has positive low correlation (11.2%) with BIST100 Equity index. On the contrary, gold has negative low correlation (-14.5%) with USD/TRY FX rate. Equity market has also got negative correlation with FX rate but correlation level is significantly higher (-64.1%) than gold has.

Table 4. *Pairwise Correlation Matrix of Gold, Equity Market and USD/TRY (2000:01-2018:05)*

	XU100USD	XAUUSD	USDTRY
Equity index (XU100USD)	1		
Gold (XAUUSD)	0,111914564	1	
USDTRY	-0,641408063	-0,144698358	1

5. Empirical analysis

We estimated conditional volatilities on gold and stock return series via standard GARCH(1,1) model and results are given in the below table. In Gold return series, probabilities of coefficients are less than 0.05 which means they are all significant. Result shows that past shocks and past volatility of gold influence current conditional volatility. Similarly, result for BIST100 also shows that past shocks and past volatility impact current conditional volatility. Moreover, their sums for both gold and equity index series are very close to unity meaning that volatility process is strongly persistent, which indicates long memory. We also examine residuals generated from GARCH(1,1) model to check whether the model is correctly specified and produce reliable volatility estimates.

Table 2. *Conditional Volatilities of Gold and Stock Prices with GARCH (1, 1)*

	Gold	Coef.	Std.Err.	z	P>IzI
Gold	Cons.	.030907	.013490	2.29	**0.02
ARCH	Arch L1.	.038015	.002231	17.04	*0.000
	Garch L1.	.953074	.002812	338.94	*0.000
	Cons.	.010701	.001589	6.73	*0.000
	BIST100	Coef.	Std.Err.	z	P>IzI
BIST100	Cons.	.120506	.028839	4.17	*0.000
ARCH	Arch L1.	.110637	.006393	17.30	*0.000
	Garch L1.	.870472	.006464	134.67	*0.000
	Cons.	.144171	.015405	9.36	*0.000

As in the ARCH model, the predicted variances are plotted below. Similar to aforementioned return series' volatility patterns, volatility change over time and stock index presents much more volatility then gold during 2001while gold is much more volatile during 2008 global financial crisis. For both series, volatility declines towards the end of the sample.

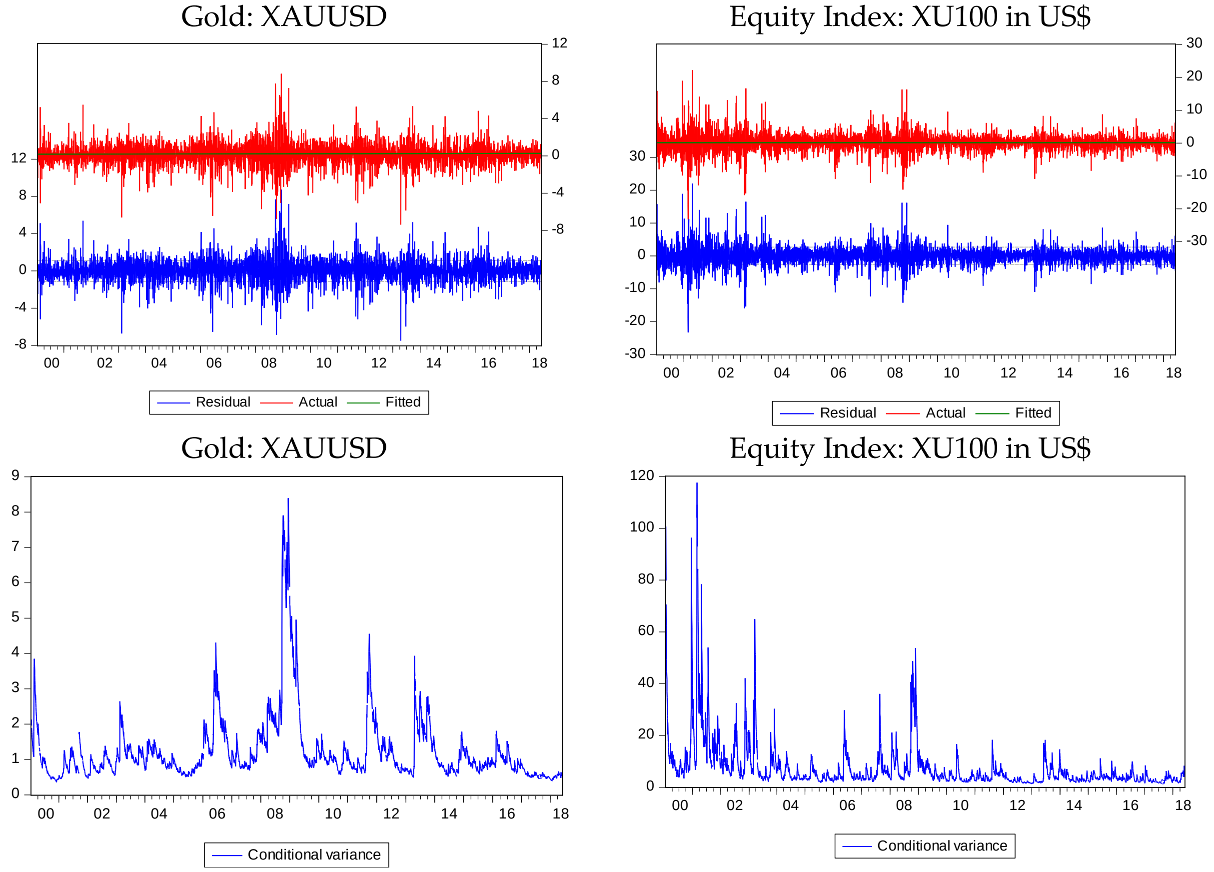

Figure 4. *Volatilitiesof the XAUUSD and the XU100USD*

The estimates represent the time-variation characteristic and clusters of volatility for both gold and equity markets. However, gold risk level is significantly lower than equity market.

6.Conclusion

The gold likes stressed market conditions and outperform alternative instruments due to its low correlation with other assets. Volatility is a very important indicator in financial market therefore, volatility forecasting is important in order to determine portfolio composition, asset management and risk measure.

In this paper, we evaluated risk profile of gold and equity markets in Turkey with GARCH volatility modeling methodology. We observe that current conditional volatility of gold returns and BIST100 is significantly impacted by its own past shocks (news) and volatility.Furthermore, GARCH model results show that short term component of volatility is weaker than the permanent component and current conditional volatility of gold prices is significantly impacted by its own past shocks and volatility. For this reason we can conclude that persistence exists in the volatility process. The results also confirms the volatility clustering that high volatilities are likely to be pursued by high ones and vice versa. Parallel to literature finding, gold is a diversification instrument because of its low correlation with stock markets and its low risk profile feature induced with low volatilities in gold markets than equity markets.

Appendix

Appendix 1- *Gold (XAUUSD)Empirical Results*

a) **Heteroskedasticity Test: ARCH**

F-statistic	167.9621	Prob. F(1,4607)	0.0000
Obs*R-squared	162.1243	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 12/01/18 Time: 00:53
Sample (adjusted): 1/05/2000 5/31/2018
Included observations: 4609 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.018504	0.053735	18.95404	0.0000
RESID^2(-1)	0.187513	0.014469	12.96002	0.0000
R-squared	0.035176	Mean dependent var		1.253875
Adjusted R-squared	0.034966	S.D. dependent var		3.495054
S.E. of regression	3.433406	Akaike info criterion		5.305416
Sum squared resid	54308.59	Schwarz criterion		5.308209
Log likelihood	-12224.33	Hannan-Quinn criter.		5.306399
F-statistic	167.9621	Durbin-Watson stat		2.028755
Prob(F-statistic)	0.000000			

Probability of coefficient less than 0.05 it means that there is ARCH effect. So we can use GARCH model for prediction of volatility.

b) **GARCH(1 1)**

Dependent Variable: XAUUSD
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/01/18 Time: 00:57
Sample: 1/04/2000 5/31/2018
Included observations: 4610
Convergence achieved after 27 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.030907	0.013490	2.291023	0.0220
	Variance Equation			
C	0.010701	0.001589	6.734532	0.0000
RESID(-1)^2	0.038015	0.002231	17.03578	0.0000
GARCH(-1)	0.953074	0.002812	338.9444	0.0000
R-squared	-0.000053	Mean dependent var		0.039038
Adjusted R-squared	-0.000053	S.D. dependent var		1.120369
S.E. of regression	1.120399	Akaike info criterion		2.895620
Sum squared resid	5785.645	Schwarz criterion		2.901204
Log likelihood	-6670.403	Hannan-Quinn criter.		2.897585
Durbin-Watson stat	2.049630			

Heteroskedasticity Test: ARCH

F-statistic	8.977521	Prob. F(1,4607)	0.0027
Obs*R-squared	8.963951	Prob. Chi-Square(1)	0.0028

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 12/01/18 Time: 01:16
Sample (adjusted): 1/05/2000 5/31/2018
Included observations: 4609 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.956409	0.036891	25.92546	0.0000
WGT_RESID^2(-1)	0.044098	0.014718	2.996251	0.0027
R-squared	0.001945	Mean dependent var		1.000561
Adjusted R-squared	0.001728	S.D. dependent var		2.298002
S.E. of regression	2.296015	Akaike info criterion		4.500661
Sum squared resid	24286.66	Schwarz criterion		4.503454
Log likelihood	-10369.77	Hannan-Quinn criter.		4.501644
F-statistic	8.977521	Durbin-Watson stat		2.000429
Prob(F-statistic)	0.002748			

Arch LM test shows there is still ARCH effect in the model.
It means that GARCH (1,1) is not suitable for XAU100.Then we used GARCH (2,0)

Heteroskedasticity Test: ARCH

F-statistic	8.977521	Prob. F(1,4607)	0.0027
Obs*R-squared	8.963951	Prob. Chi-Square(1)	0.0028

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 12/01/18 Time: 01:16
Sample (adjusted): 1/05/2000 5/31/2018
Included observations: 4609 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.956409	0.036891	25.92546	0.0000
WGT_RESID^2(-1)	0.044098	0.014718	2.996251	0.0027
R-squared	0.001945	Mean dependent var		1.000561
Adjusted R-squared	0.001728	S.D. dependent var		2.298002
S.E. of regression	2.296015	Akaike info criterion		4.500661
Sum squared resid	24286.66	Schwarz criterion		4.503454
Log likelihood	-10369.77	Hannan-Quinn criter.		4.501644
F-statistic	8.977521	Durbin-Watson stat		2.000429
Prob(F-statistic)	0.002748			

Dependent Variable: XAUUSD

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/01/18 Time: 01:19
Sample: 1/04/2000 5/31/2018
Included observations: 4610
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-2)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.048618	0.014915	3.259749	0.0011
	Variance Equation			
C	0.930250	0.015889	58.54757	0.0000
RESID(-1)^2	0.110814	0.009193	12.05452	0.0000
RESID(-2)^2	0.148071	0.011967	12.37293	0.0000
R-squared	-0.000073	Mean dependent var	0.039038	
Adjusted R-squared	-0.000073	S.D. dependent var	1.120369	
S.E. of regression	1.120410	Akaike info criterion	3.004194	
Sum squared resid	5785.763	Schwarz criterion	3.009778	
Log likelihood	-6920.666	Hannan-Quinn criter.	3.006159	
Durbin-Watson stat	2.049589			

Arch LM test shows there is no arch effect in the model.
It means that GARCH (2,0) is best model for XAUSD.

Appendix 2. *XU100USD*

a) **Heteroskedasticity Test: ARCH**

Heteroskedasticity Test: ARCH			
F-statistic	440.0369	Prob. F(1,4607)	0.0000
Obs*R-squared	401.8457	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 12/01/18 Time: 01:37
Sample (adjusted): 1/05/2000 5/31/2018
Included observations: 4609 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.081176	0.326040	15.58454	0.0000
RESID^2(-1)	0.291419	0.013892	20.97706	0.0000
R-squared	0.087187	Mean dependent var	7.191596	
Adjusted R-squared	0.086989	S.D. dependent var	22.03475	
S.E. of regression	21.05456	Akaike info criterion	8.932545	
Sum squared resid	2042258.	Schwarz criterion	8.935338	
Log likelihood	-20583.05	Hannan-Quinn criter.	8.933528	
F-statistic	440.0369	Durbin-Watson stat	2.063832	
Prob(F-statistic)	0.000000			

There is ARCH effect.
So we can use GARCH model for prediction of volatility.

a) **GARCH(1,1)**

Dependent Variable: XU100USD				
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)				
Date: 12/01/18 Time: 01:42				
Sample: 1/04/2000 5/31/2018				
Included observations: 4610				
Convergence achieved after 23 iterations				
Coefficient covariance computed using outer product of gradients				
Presample variance: backcast (parameter = 0.7)				
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.120506	0.028839	4.178589	0.0000
Variance Equation				
C	0.144171	0.015405	9.358474	0.0000
RESID(-1)^2	0.110637	0.006393	17.30637	0.0000
GARCH(-1)	0.870472	0.006464	134.6689	0.0000
R-squared	-0.001107	Mean dependent var		0.030958
Adjusted R-squared	-0.001107	S.D. dependent var		2.691877
S.E. of regression	2.693366	Akaike info criterion		4.503306
Sum squared resid	33434.70	Schwarz criterion		4.508890
Log likelihood	-10376.12	Hannan-Quinn criter.		4.505271
Durbin-Watson stat	1.898541			
Heteroskedasticity Test: ARCH				
F-statistic	1.201293	Prob. F(1,4607)		0.2731
Obs*R-squared	1.201501	Prob. Chi-Square(1)		0.2730
Test Equation:				
Dependent Variable: WGT_RESID^2				
Method: Least Squares				
Date: 12/01/18 Time: 01:44				
Sample (adjusted): 1/05/2000 5/31/2018				
Included observations: 4609 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.982629	0.033624	29.22424	0.0000
WGT_RESID^2(-1)	0.016146	0.014731	1.096035	0.2731
R-squared	0.000261	Mean dependent var		0.998755
Adjusted R-squared	0.000044	S.D. dependent var		2.052624
S.E. of regression	2.052579	Akaike info criterion		4.276505
Sum squared resid	19409.66	Schwarz criterion		4.279298
Log likelihood	-9853.205	Hannan-Quinn criter.		4.277488
F-statistic	1.201293	Durbin-Watson stat		2.000065
Prob(F-statistic)	0.273121			

Probability more than 0.05 we can accept that there is no ARCH effect in that model.

ARCH (1,1) is best model for stock market return.

Appendix 3. *USDTRY*

a) Heteroskedasticity Test: ARCH

Heteroskedasticity Test: ARCH			
F-statistic	13.60529	Prob. F(1,4607)	0.0002
Obs*R-squared	13.57111	Prob. Chi-Square(1)	0.0002

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 12/01/18 Time: 01:55
Sample (adjusted): 1/05/2000 5/31/2018
Included observations: 4609 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.268905	0.403416	3.145396	0.0017
RESID^2(-1)	0.054263	0.014711	3.688534	0.0002
R-squared	0.002944	Mean dependent var		1.341694
Adjusted R-squared	0.002728	S.D. dependent var		27.39239
S.E. of regression	27.35500	Akaike info criterion		9.456110
Sum squared resid	3447401.	Schwarz criterion		9.458902
Log likelihood	-21789.61	Hannan-Quinn criter.		9.457093
F-statistic	13.60529	Durbin-Watson stat		2.001861
Prob(F-statistic)	0.000228			

There is ARCH effect.
So we can use GARCH model for prediction of volatility.

a) GARCH(1,1)

Dependent Variable: USDTRY
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/01/18 Time: 01:56
Sample: 1/04/2000 5/31/2018
Included observations: 4610
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.097545	0.006903	-14.13035	0.0000
	Variance Equation			
C	0.184399	0.009430	19.55515	0.0000
RESID(-1)^2	1.435426	0.027174	52.82384	0.0000
GARCH(-1)	0.242191	0.009748	24.84511	0.0000
R-squared	-0.016666	Mean dependent var		0.051980
Adjusted R-squared	-0.016666	S.D. dependent var		1.158361
S.E. of regression	1.167974	Akaike info criterion		2.812254
Sum squared resid	6287.425	Schwarz criterion		2.817838
Log likelihood	-6478.245	Hannan-Quinn criter.		2.814219
Durbin-Watson stat	1.837880			

Coefficients of GARCH (1,1) summing up to more than one is an indication that a stationary GARCHmodel is unlikely to fit the data well. However, there is a great variety of GARCH model versions,

Heteroskedasticity Test: ARCH				
F-statistic	0.012304	Prob. F(1,4607)		0.9117
Obs*R-squared	0.012309	Prob. Chi-Square(1)		0.9117
Test Equation:				
Dependent Variable: WGT_RESID^2				
Method: Least Squares				
Date: 12/01/18 Time: 01:56				
Sample (adjusted): 1/05/2000 5/31/2018				
Included observations: 4609 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.001703	0.240081	4.172351	0.0000
WGT_RESID^2(-1)	-0.001634	0.014733	-0.110922	0.9117
R-squared	0.000003	Mean dependent var		1.000069
Adjusted R-squared	-0.000214	S.D. dependent var		16.26655
S.E. of regression	16.26830	Akaike info criterion		8.416747
Sum squared resid	1219277.	Schwarz criterion		8.419540
Log likelihood	-19394.39	Hannan-Quinn criter.		8.417730
F-statistic	0.012304	Durbin-Watson stat		2.000003
Prob(F-statistic)	0.911683			

There is no ARCH effect, GARCH (1,1) is the best model for USDTRY.

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