International Journal of Economics, Commerce and Management
United Kingdom Vol. VI, Issue 11, November 2018
http://ijecm.co.uk/ ISSN 2348 0386

MODELING EXCHANGE RATE VOLATILITY OF UZBEK SUM BY USING ARCH FAMILY MODELS

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Abstract

a number of models have been developed in empirical finance literature to investigate this volatility across different countries. As pioneered applied models to estimate exchange rate volatility are the ARCH (Autoregressive Conditional Heteroscedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models. This paper examines the performance of ARCH family models for the weekly USD/UZS and EUR/UZS exchange rate data sets within the time period from 2000 to 2018 July 17. Evaluation of models through standard information criteria showed that the PARCH model is the best fitted model for the weekly USD/UZS exchange rate return volatility and IGARCH model for the weekly EUR/UZS exchange rate return volatility. In accordance to the estimated models there is empirical evidence that negative and positive shocks imply a different next period volatility of the weekly exchange rate returns.

Keywords: ARCH family models, exchange rate, USD/UZS, EUR/UZS

Note: The findings, interpretations, and conclusions expressed in this paper are entirely authors view. They do not necessarily represent the views of the Central Bank of Uzbekistan.

INTRODUCTION

Over the past few decades, exchange rate movements and fluctuations have become an important subject of macroeconomic analysis and have received a great deal of interest from academicians, researchers, financial economists and policy makers. Especially there has been an extensive debate about the topic of exchange rate volatility and its potential influence on welfare, inflation, international trade and degree of external sector competitiveness of the economy. Consequently, a number of models have been developed in empirical finance literature to investigate this volatility across different countries. As pioneered applied models to estimate exchange rate volatility are the ARCH (Autoregressive Conditional Heteroscedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models. ARCH model advanced by Engle (1982) and GARCH model was developed independently by Bollerslev (1986) and Taylor (1986).

However, the ARCH class of models has subsequently found especially wide use in characterizing time-varying financial market volatility. An ARCH (q) model is estimated using ordinary least squares. As in many research studies that use ARCH family models for exchange rate analysis, we test in this article different models in order to find the best fitted one for our data series. After choosing the best model for our data series different tests are applied on it. We checked the ARCH family model for serial correlation, heteroskedasticity of the model and we also checked if the residuals are normally distributed or not. Finally we take a look at the volatility, which is measured by the conditional standard deviation.

LITERATURE REVIEW

ARCH family models are frequently used for exchange rate time series. Most of the articles in this area of the literature deal with the analysis of the exchange rate volatility or with the forecast of the exchange rates. As mentioned above the first ARCH model was introduced by Engle in order to describe U.K. inflationary uncertainty. The main purpose of the ARCH model is to estimate the conditional variance of a time series. Engle described the conditional variance by a simple quadratic function of its lagged values. However, the ARCH family models have subsequently found especially wide use in characterizing time-varying financial market volatility. Particularly this model used to define heteroskedasticity of the conditional variance of the disturbance term to the linear combination of the squared disturbances in the recent past.

The GARCH model is a generalized ARCH model which is modeling the conditional variance by its own lagged values and the square of the lagged values of the innovations or shocks. Nelson (1991) formulated the Exponential GARCH (EGARCH - Exponential Generalized Autoregressive Conditional Heteroskedasticity) model by extending the GARCH model to capture news in the form of leverage effects. The model explicitly allows for asymmetries in the relationship between return and volatility. Afterwards, the GARCH model extension was developed to test for this asymmetric news impact (Glosten, Jagannathan, Runkle, 1993; Zakoïan, 1994).

Olowe (2009) modeled volatility of Naira/US Dollar exchange rates on a sample of monthly data from 1970 to 2007. The paper concluded that the best fitted models are the Asymmetric Power ARCH (APARCH) and the Threshold Symmetric GARCH (TSGARCH) models. Another model is called the integrated GARCH (IGARCH) model which is estimates of the standard linear GARCH (p, q) model often results in the sum of the estimated ai and βi coefficients being close to unity.

There are various ARCH family models have been applied by researchers to analyze the volatility of exchange rates in different countries. For example, Ngowani (2012) found out GARCH (1, 1) model as the best fitted model for the USD/RMB exchange rate volatility in Zambia case. Ullah et al. (2012) found GARCH (1, 1) as the best fitted model describing the Rupee behavior pattern in Pakistan case. Arabi (2012) modeled the Sudanese pound daily exchange rate volatility and found EGARCH (1, 1) to be the best fitted model indicating the existence of the leverage effect. Cağlayan et al. (2013) found EGARCH as the best forecasting model for Mexico.

METHODOLOGY

Since time series are being modeled, stationary properties of the observed time series needs to be checked first. In order to test stationary properties of the observed time series there were performed an Augmented Dickey–Fuller test (ADF) for a unit root in a time series (Dickey, Fuller, 1981). Afterwards, using the ordinary least squares method (OLS) as an estimator, the foreign exchange rate moving pattern is estimated. The foreign exchange rate moving pattern might be an autoregressive (AR) process, moving average (MA) process or combination of AR and MA processes (ARMA) and integrated model (I) autoregressive integrated moving average (ARIMA) model, which combine all three of the models above mentioned. For the purposes of this study the mean equation is modified to include appropriate AR and MA terms to control for autocorrelation in the data. For example, in ARMA (1, 1) process pattern would be:

$$Y_t = \sum_{i=1}^{p} a_i * Y_{t-1} + \varepsilon_t + \sum_{i=1}^{q} \beta_i * \varepsilon_{t-1}$$

Where Y_t is a time series being modeled.

In accordance with autocorrelation and partial correlation within correlogram for each time series, a process pattern is assumed and the process pattern assumption for each time series is verified through diagnostic checking. Based on heteroscedasticity test results on residuals for each of the estimated foreign exchange rate moving patterns, further steps are performed. Heteroscedasticity of residuals in the estimated foreign exchange rate moving pattern is tested through the ARCH test, i.e. Lagrange multiplier test (ARCH LM Test) in order to assess the significance of ARCH effects. If the ARCH effect is significant, several ARCH based models will be tested and compared. Based on the results, the tested models are specified.

RESULTS AND DISCUSSION

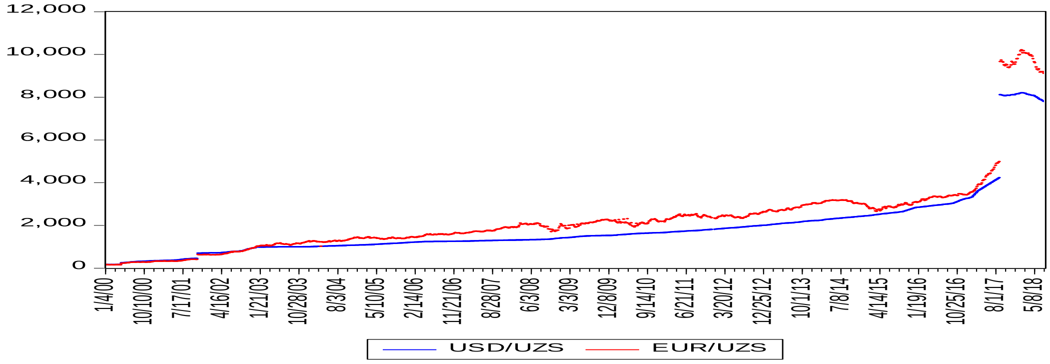
First we need to show the descriptive statistics on our data in order to observe the mean, median, maximum, minimum, standard deviation, skewness, kurtosis, Jaque-Bera, probability, Sum, sum sq. dev. and the number of observations. Interesting to see is that the difference between the minimum and the maximum values is rather significant (Table 1).

Table 1. Descriptive statistics for the USD/UZS and EUR/UZS nominal weekly exchange rates

	USD_UZS	**EUR_UZS**
Mean	1860.554	2294.846
Median	1436.440	2039.880
Maximum	8188.330	10196.85
Minimum	140.4600	137.5000
Std. Dev.	1600.874	1906.005
Skewness	2.702465	2.614039
Kurtosis	10.93214	10.91598
Jarque-Bera	3727.514	3641.072
Probability	0.000000	0.000000
Sum	1806598.	2228296.
SumSq. Dev.	2.49E+09	3.52E+09
Observations	971	971

From figure 1 it can be seen that the data is non-stationary, but we will run the ADF test to make sure. Also, figure shows that there were increasing trends of the time series can be noticed. Both currencies show evidence of fat tails since their kurtosis exceed 3 coefficient. The extremely large Jarque-Bera (JB) statistic for USD and Euro indicates non–normality of most of the series.

Figure 1. USD/UZS and EUR/UZS weekly nominal exchange rates over the time period 01.2000 - 07.2018



In accordance with the ADF test results shown in Table 2, one can conclude that the weekly exchange rate return of the USD/UZS and EUR/UZS is a stationary time series around zero.

Table 2. Augmented Dickey–Fuller test (ADF) on the observed time series

Variable	t-Statistics	p-value
r_{t-USD}	-30.67991	0.0000
r_{t-EUR}	-32.97491	0.0000

The existence of the degree of autocorrelation and the partial autocorrelation between the data considered and the results of the Ljung-Box Q test performed on the squared residuals were verified (see Appendix). Because of the p-value (all zero), the hypothesis of zero correlation between the data series was rejected, which is also demonstrated by the autocorrelation values that are different from zero. In regards to autocorrelation and partial autocorrelation, the following assumptions are made:

- weekly USD/UZS exchange rate return time series (r_{t-USD}) can be modeled as an AR (1) process since the values of the autocorrelations decrease but never nullify and at the same time the partial autocorrelation is relevant for first term.
- weekly EUR/UZS exchange rate return time series (r_{t-EUR}) can be modeled as an AR (1) process since the values of the autocorrelations decrease but never nullify and at the same time the partial autocorrelation is relevant for first term.

According to the above-stated assumptions, the USD/UZS and the EUR/UZS weekly return exchange rate mean equations are estimated. After removing non-significant components of the model, the estimated weekly exchange rate return models for the USD/UZS and the EUR/UZS are presented in Table 3 and Table 4.

Table 3. Estimation results for AR (1) weekly exchange rate return of the USD/UZS (mean equation)

Variable	Coefficient	Prob.
AR (1)	0.004144	0.0000

Afterwards, the diagnostic checking results using the Breusch-Godfrey Serial Correlation LM Test and correlogram show serial correlation among residuals in the estimated model in Table 3and Table 4 that ARCH effect in residuals of the mean equation is significant (p-value amounts 0.0000).

Table 4. Estimation results for AR (1) weekly exchange rate return of the EUR/UZS (mean equation)

Variable	Coefficient	Prob.
AR (1)	0.004288	0.0001

The figure 2 and 3 also shows that the data is stationary in 1st difference for the USD/UZS and EUR/UZS weekly exchange rate return volatility. The 1st difference (x_t - x_{t-1}) is generally used in order to transform non-stationary data into stationary data.

Figure 2. USD/UZS weekly exchange rates over the time period 01.2000 - 07.2018 in 1st difference

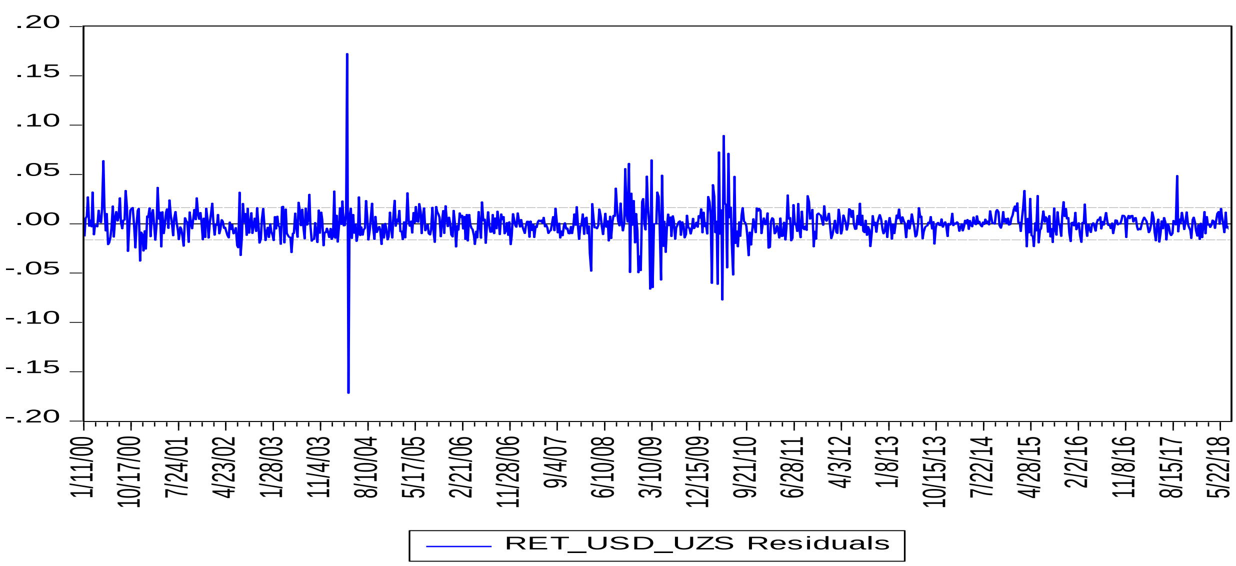
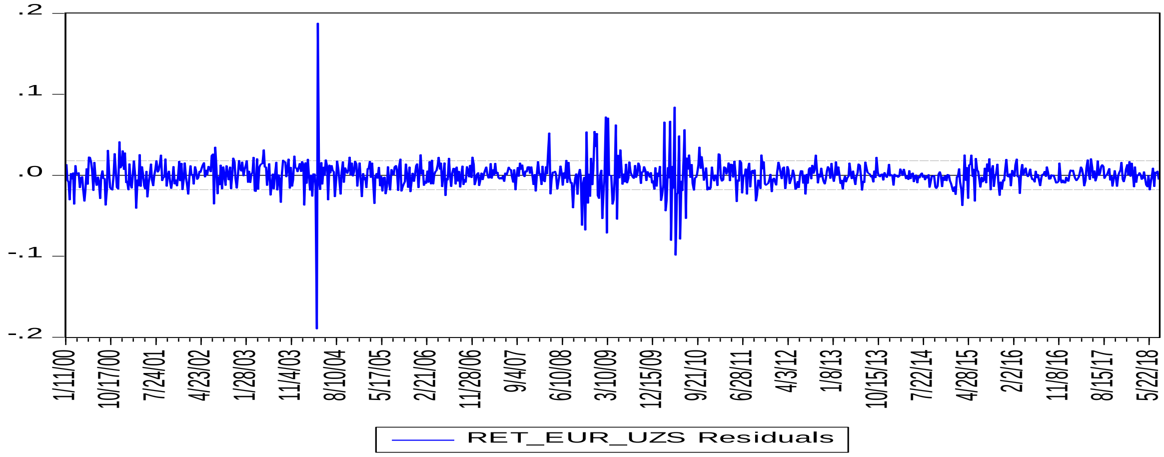


Figure 3. EUR/UZS weekly exchange rates over the time period 01.2000 - 07.2018 in 1st difference



Since the ARCH effect is significant, ARCH family models can be estimated. Table 5 and 6 shows mean and variance equations estimate for the USD/UZS and EUR/UZS weekly exchange rate returns using Normal distribution. In order to find the best model we need to look at the AIC - Akaike information criterion and SIC - Schwarz information criterion. Lower the value of AIC and SC information criterion, better fitted is the model. In our case PARCH model is a best fitted model for the USD/UZS weekly exchange rate return and EGARCH model for the EUR/UZS weekly exchange rate return.

Table 5. Mean and variance equation estimates for the USD/UZS exchange rate return – Normal distribution

Parameter	ML-ARCH (5, 0)	GARCH/TARCH (1,1)	EGARCH (1, 1)	IGARCH (1, 1)	PARCH (1, 1)
ω	0.003146	0.003914	0.006685	0.024086	0.003687
	(0.2323)	(0.4090)	(0.0000)	(0.0000)	(0.0000)
α	-0.001976	-0.001976	-1.239450	0.000626	0.0388098
	(0.4004)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β		0.799663	1.086139	0.999374	0.516183
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\alpha + \beta$		0.797687	0.153311	1.000000	0.904281
ARCH-LM Test (ARCH effect)	(0.9698)	(0.9787)	(0.9912)	(0.9253)	(0.9571)
AIC	-4,238754	-4.238764	-4.541821	-3.550789	-6.553197
SC	-4,203528	-4.218634	-4.516660	-3.540725	-6.523003
Obs	969	969	969	969	969

In parentheses shows p-value.

Table 6. Mean and variance equation estimates for the EUR/UZS exchange rate return – Normal distribution

Parameter	ML-ARCH (5, 0)	GARCH/TARCH (1,1)	EGARCH (1, 1)	IGARCH (1, 1)	PARCH (1, 1)
ω	0.003874	0.004612	0.004097	0.020014	0.003952
	(0.0174)	(0.0202)	(0.0292)	(0.0000)	(0.0440)
α	0.089168	-0.002713	-0.052184	0.000723	0.002108
	(0.0014)	(0.0000)	(0.0578)	(0.0000)	(1.0000)
β		0.840555	0.508162	0.999277	0.992191
		(0.0000)	(0.0000)	(0.0000)	(0.9999)
$\alpha + \beta$		0.837842	0.455978	1.000000	0.994299
ARCH-LM Test (ARCH effect)	(0.9390)	(0.8997)	(0.9073)	(0.9748)	(0.9329)
AIC	-3.921280	-3.917686	-3.930037	-3.462294	-3.927328
SC	-3.886054	-3.897557	-3.904876	-3.452230	-3.897134
Obs	969	969	969	969	969

In parentheses shows p-value.

After that we need to check the residuals of this model. Looking at the figure 3 at the residuals plot, we can observe that there are long periods with low fluctuations and also long periods with high fluctuations, meaning that periods of low volatility tend to be followed by periods of low volatility for a prolonged period and periods of high volatility are followed by periods of high volatility for a prolonged period.

Figure 4. Residuals of the model (USD/UZS)

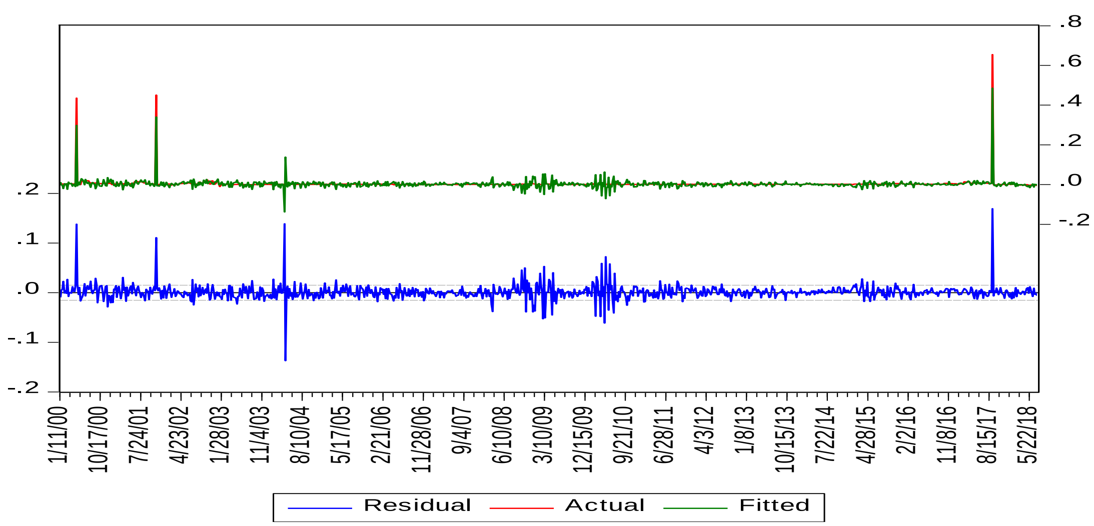
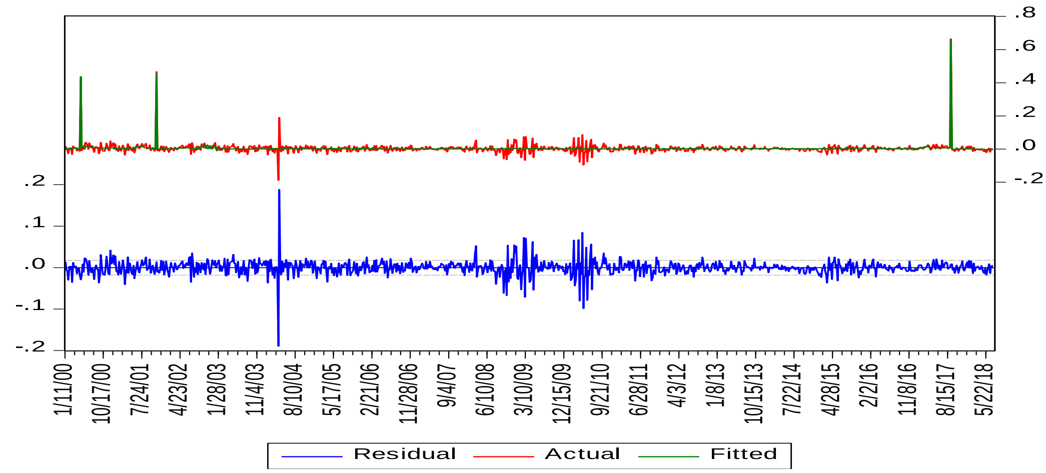


Figure 5. Residuals of the model (EUR/UZS)



CONCLUSIONS

Out of compared Akaike information criterion and Schwarz Criterion for all of the specified volatility models one can say that PARCH (1,1) is the best fitted model representing the weekly USD/UZS exchange rate return volatility since it has the lowest AIC and SC values. In case of EUR/UZS weekly exchange rate return volatility the best fitted model is EGARCH since it has the lowest AIC and SC values.

In accordance to the PARCH (1, 1) estimated parameters in Table 5 and 6 one can see that the ARCH and GARCH coefficients are statistically significant. The sum of these coefficients is 0.90 and 0.99 which indicates that shocks to volatility have a persistent effect on the conditional variance. If the sum of the ARCH and GARCH coefficients equals unity (IGARCH case) shocks will have a permanent effect. In that case the conditional variance does not converge on a constant unconditional variance in the long run. The IGARCH model assumes a symmetric response of volatility to past shocks for UZS exchange rate return.

In the design of appropriate exchange rate policies, Uzbekistan's monetary authorities should take into account key events both domestically and internationally that are likely to affect the fluctuations of the Uzbek sum against the USD dollar and Euro to incorporate significant events in the estimation of their currency models as well as other asset prices.

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APPENDICES

ARCH Model

Dependent Variable: RET_USD_UZS

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 08/13/18 Time: 19:04

Sample: 1/11/2000 7/17/2018

Includedobservations: 969

Convergenceachievedafter 92 iterations

Coefficient covariance computed using outer product of gradients

Presamplevariance: backcast (parameter = 0.7)

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-2)^2 + C(5)*RESID(-3)^2 + C(6)*RESID(-4)^2 + C(7)*RESID(-5)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003146	0.002634	1.194479	0.2323
	VarianceEquation			
C	0.000855	8.60E-06	99.34809	0.0000
RESID(-1)^2	-0.001976	0.002350	-0.840830	0.4004
RESID(-2)^2	-0.001960	0.002306	-0.849868	0.3954
RESID(-3)^2	-0.001970	0.002319	-0.849669	0.3955
RESID(-4)^2	-0.001980	0.002285	-0.866471	0.3862

RESID(-5)^2	-0.001974	0.002845	-0.693882	0.4878

R-squared	-0.001173	Meandependentvar	0.004144
Adjusted R-squared	-0.001173	S.D. dependentvar	0.029148
S.E. ofregression	0.029165	Akaikeinfocriterion	-4.238754
Sumsquaredresid	0.823388	Schwarzcriterion	-4.203528
Loglikelihood	2060.676	Hannan-Quinncriter.	-4.225345
Durbin-Watsonstat	1.971741		

Dependent Variable: RET_EUR_UZS

Method: ML – ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 08/13/18 Time: 19:07

Sample: 1/11/2000 7/17/2018

Includedobservations: 969

Convergenceachievedafter 71 iterations

Coefficient covariance computed using outer product of gradients

Presamplevariance: backcast (parameter = 0.7)

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-2)^2 + C(5)*RESID(-3)^2+ C(6)*RESID(-4)^2 + C(7)*RESID(-5)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003874	0.001630	2.377097	0.0174
	VarianceEquation			
C	0.001128	8.20E-06	137.4970	0.0000
RESID(-1)^2	0.089168	0.027952	3.190037	0.0014
RESID(-2)^2	-0.002334	0.003088	-0.755823	0.4498
RESID(-3)^2	-0.002539	0.003236	-0.784598	0.4327
RESID(-4)^2	-0.002006	0.004131	-0.485666	0.6272
RESID(-5)^2	-0.002493	0.006290	-0.396311	0.6919

R-squared	-0.000147	Meandependentvar	0.004288
Adjusted R-squared	-0.000147	S.D. dependentvar	0.034195
S.E. ofregression	0.034197	Akaikeinfocriterion	-3.921280
Sumsquaredresid	1.132035	Schwarzcriterion	-3.886054
Loglikelihood	1906.860	Hannan-Quinncriter.	-3.907871
Durbin-Watsonstat	2.117559		

GARCH Model

Dependent Variable: RET_USD_UZS

Method: ML – ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 08/13/18 Time: 15:32

Sample: 1/11/2000 7/17/2018

Includedobservations: 969

Convergenceachievedafter 48 iterations

Coefficient covariance computed using outer product of gradients

Presamplevariance: backcast (parameter = 0.7)

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

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003914	0.004741	0.825614	0.4090
	VarianceEquation			
C	0.000171	2.75E-05	6.233151	0.0000
RESID(-1)^2	-0.001976	0.000430	-4.596360	0.0000
GARCH(-1)	0.799663	0.030477	26.23824	0.0000

R-squared	-0.000062	Meandependentvar	0.004144
Adjusted R-squared	-0.000062	S.D. dependentvar	0.029148
S.E. ofregression	0.029149	Akaikeinfocriterion	-4.238764
Sumsquaredresid	0.822474	Schwarzcriterion	-4.218634
Loglikelihood	2057.681	Hannan-Quinncriter.	-4.231101
Durbin-Watsonstat	1.973931		

Dependent Variable: RET_EUR_UZS

Method: ML – ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 08/13/18 Time: 18:23

Sample: 1/11/2000 7/17/2018

Includedobservations: 969

Convergenceachievedafter 59 iterations

Coefficient covariance computed using outer product of gradients

Presamplevariance: backcast (parameter = 0.7)

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

Variable	Coefficient	Std. Error	z-Statistic	Prob.

C	0.004612	0.001986	2.321880	0.0202
	VarianceEquation			
C	0.000189	2.39E-05	7.935713	0.0000
RESID(-1)^2	-0.002713	0.000570	-4.762760	0.0000
GARCH(-1)	0.840555	0.020124	41.76976	0.0000

R-squared	-0.000090	Meandependentvar	0.004288
Adjusted R-squared	-0.000090	S.D. dependentvar	0.034195
S.E. ofregression	0.034196	Akaikeinfocriterion	-3.917686
Sumsquaredresid	1.131971	Schwarzcriterion	-3.897557
Loglikelihood	1902.119	Hannan-Quinncriter.	-3.910024
Durbin-Watsonstat	2.117680		

EGARCH Model

Dependent Variable: RET_USD_UZS

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 08/13/18 Time: 19:46

Sample: 1/11/2000 7/17/2018

Includedobservations: 969

Failure to improve likelihood (non-zero gradients) after 25 iterations

Coefficient covariance computed using outer product of gradients

Presamplevariance: backcast (parameter = 0.7)

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)

*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.006685	6.52E-06	1025.463	0.0000
	VarianceEquation			
C(2)	-6.960357	0.004200	-1657.207	0.0000
C(3)	-1.239450	0.005137	-241.2831	0.0000
C(4)	1.086139	0.005436	199.7946	0.0000
C(5)	0.012973	0.000357	36.33850	0.0000

R-squared	-0.007607	Meandependentvar	0.004144
Adjusted R-squared	-0.007607	S.D. dependentvar	0.029148
S.E. ofregression	0.029259	Akaikeinfocriterion	-4.541821
Sumsquaredresid	0.828679	Schwarzcriterion	-4.516660
Loglikelihood	2205.512	Hannan-Quinncriter.	-4.532244
Durbin-Watsonstat	1.959151		

Dependent Variable: RET_EUR_UZS

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 08/13/18 Time: 17:58

Sample: 1/11/2000 7/17/2018

Includedobservations: 969

Convergenceachievedafter 39 iterations

Coefficient covariance computed using outer product of gradients

Presamplevariance: backcast (parameter = 0.7)

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)

*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.004097	0.001879	2.180479	0.0292
	VarianceEquation			
C(2)	-3.312303	0.727443	-4.553351	0.0000
C(3)	-0.052184	0.027508	-1.897079	0.0578
C(4)	-0.168027	0.029959	-5.608557	0.0000
C(5)	0.508162	0.108508	4.683168	0.0000

R-squared	-0.000031	Meandependentvar	0.004288
Adjusted R-squared	-0.000031	S.D. dependentvar	0.034195
S.E. ofregression	0.034195	Akaikeinfocriterion	-3.930037
Sumsquaredresid	1.131904	Schwarzcriterion	-3.904876
Loglikelihood	1909.103	Hannan-Quinncriter.	-3.920460
Durbin-Watsonstat	2.117804		

IGARCH Model

Dependent Variable: RET_USD_UZS

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 08/13/18 Time: 15:38

Sample: 1/11/2000 7/17/2018

Includedobservations: 969

Convergenceachievedafter 22 iterations

Coefficient covariance computed using outer product of gradients

Presamplevariance: backcast (parameter = 0.7)

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

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RET_EUR_UZS	0.911716	0.001927	473.0543	0.0000
C	0.000359	0.000265	1.351246	0.1766
	VarianceEquation			
RESID(-1)^2	0.103898	0.006413	16.20056	0.0000
GARCH(-1)	0.896102	0.006413	139.7262	0.0000
R-squared	0.681465	Meandependentvar		0.004144
Adjusted R-squared	0.681135	S.D. dependentvar		0.029148
S.E. ofregression	0.016459	Akaikeinfocriterion		-5.717804
Sumsquaredresid	0.261971	Schwarzcriterion		-5.702707
Loglikelihood	2773.276	Hannan-Quinncriter.		-5.712057
Durbin-Watsonstat	2.390284			

Dependent Variable: RET_EUR_UZS

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 08/13/18 Time: 15:40

Sample: 1/11/2000 7/17/2018

Includedobservations: 969

Convergenceachievedafter 20 iterations

Coefficient covariance computed using outer product of gradients

Presamplevariance: backcast (parameter = 0.7)

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

Variable	Coefficient	Std. Error	z-Statistic	Prob.

RET_USD_UZS	1.007906	0.010424	96.69269	0.0000
C	0.000349	0.000278	1.253407	0.2101
	VarianceEquation			
RESID(-1)^2	0.115186	0.007193	16.01389	0.0000
GARCH(-1)	0.884814	0.007193	123.0122	0.0000

R-squared	0.728147	Meandependentvar	0.004288
Adjusted R-squared	0.727866	S.D. dependentvar	0.034195
S.E. ofregression	0.017838	Akaikeinfocriterion	-5.611347
Sumsquaredresid	0.307702	Schwarzcriterion	-5.596250
Loglikelihood	2721.698	Hannan-Quinncriter.	-5.605600
Durbin-Watsonstat	2.408458		

PARCH Model

Dependent Variable: RET_USD_UZS

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 08/14/18 Time: 17:18

Sample: 1/11/2000 7/17/2018

Includedobservations: 969

Failure to improve likelihood (non-zero gradients) after 180 iterations

Coefficient covariance computed using outer product of gradients

Presamplevariance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(6) = C(2) + C(3)*(ABS(RESID(-1)) - C(4)*RESID(
-1))^C(6) + C(5)*@SQRT(GARCH(-1))^C(6)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003687	3.04E-05	121.3135	0.0000
	VarianceEquation			
C(2)	0.003371	1.78E-05	189.1390	0.0000
C(3)	-0.076403	0.000278	-275.0495	0.0000
C(4)	0.388098	0.009333	41.58373	0.0000
C(5)	1.004529	5.88E-06	170727.5	0.0000
C(6)	0.516183	7.36E-05	7015.668	0.0000

R-squared	-0.000246	Meandependentvar	0.004144
Adjusted R-squared	-0.000246	S.D. dependentvar	0.029148

S.E. ofregression	0.029152	Akaikeinfocriterion	-6.553197
Sumsquaredresid	0.822625	Schwarzcriterion	-6.523003
Loglikelihood	3181.024	Hannan-Quinncriter.	-6.541704
Durbin-Watsonstat	1.973568		

Dependent Variable: RET_EUR_UZS

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 08/14/18 Time: 15:53

Sample: 1/11/2000 7/17/2018

Includedobservations: 969

Convergence not achieved after 500 iterations

Coefficient covariance computed using outer product of gradients

Presamplevariance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(6) = C(2) + C(3)*(ABS(RESID(-1)) - C(4)*RESID(
-1))^C(6) + C(5)*@SQRT(GARCH(-1))^C(6)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003952	0.001962	2.014096	0.0440
	VarianceEquation			
C(2)	1.94E-07	5.38E-06	0.036069	0.9712
C(3)	0.002108	64.78851	3.25E-05	1.0000
C(4)	0.992191	13426.02	7.39E-05	0.9999
C(5)	-0.007329	0.609941	-0.012017	0.9904
C(6)	4.560149	8.163228	0.558621	0.5764

R-squared	-0.000097	Meandependentvar	0.004288
Adjusted R-squared	-0.000097	S.D. dependentvar	0.034195
S.E. ofregression	0.034196	Akaikeinfocriterion	-3.927328
Sumsquaredresid	1.131979	Schwarzcriterion	-3.897134
Loglikelihood	1908.790	Hannan-Quinncriter.	-3.915834
Durbin-Watsonstat	2.117665		

Correlogram specification: RET_USD/UZS

Date: 08/14/18 Time: 18:26

Sample: 1/11/2000 7/17/2018

Includedobservations: 969

	AC	PAC	Q-Stat	Prob
1	0.013	0.013	0.1627	0.687
2	0.009	0.009	0.2485	0.883
3	0.010	0.010	0.3461	0.951
4	0.006	0.006	0.3847	0.984
5	0.016	0.015	0.6275	0.987
6	0.016	0.015	0.8763	0.990
7	0.016	0.015	1.1222	0.993
8	0.016	0.015	1.3585	0.995
9	0.015	0.014	1.5729	0.997
10	0.016	0.014	1.8114	0.998
11	0.017	0.015	2.0873	0.998
12	0.017	0.016	2.3816	0.999
13	0.012	0.010	2.5141	0.999
14	0.012	0.010	2.6536	1.000
15	0.011	0.009	2.7697	1.000

Correlogram specification: RET_ EUR/UZS

Date: 08/14/18 Time: 18:29 Includedobservations: 969

	AC	PAC	Q-Stat	Prob
1	-0.059	-0.059	3.3930	0.065
2	0.003	-0.001	3.3994	0.183
3	-0.019	-0.019	3.7546	0.289
4	0.036	0.034	5.0024	0.287
5	0.036	0.041	6.2958	0.278
6	0.007	0.012	6.3485	0.385
7	0.015	0.018	6.5830	0.474
8	-0.019	-0.017	6.9455	0.543
9	0.035	0.030	8.1275	0.521
10	0.005	0.008	8.1550	0.614
11	0.022	0.021	8.6495	0.654
12	0.002	0.006	8.6526	0.732
13	0.008	0.007	8.7157	0.794
14	-0.026	-0.027	9.3774	0.806
15	0.024	0.019	9.9583	0.822