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*INVESTIGATING THE EVOLUTION OF RON/EUR EXCHANGE RATE: THE CHOICE OF APPROPRIATE MODEL**

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Abstract

The volatility of currency exchange rates can be considered as an useful measure of uncertainty about the economic environment of a country.The paper aims to investigate the evolution of the daily RON/EURO exchange rate between January 5th, 2009 and October 12, 2012. Several appropriate models are used and discussed, from ARCH, GARCH models to EGARCH and TGARCH models, trying to capture the main features of the analysed data. The periods of low and high volatility are discussed and analysed in correlation to the negative and positive shocks. The used models are able to model asymmetries in volatility forecasts allowing for asymmetric responses in volatility to the positive and negative shocks.

Keywords: exchange rate, volatility, GARCH models
JEL Classification: C53, E17

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1. Introduction

The evolution of the exchange rate evolution, as an empirical financial time series, presents various forms of non linear dynamics.

The variance changes over time and large changes tend to followed by large changes of either sign. Engle showed (1982) that large and small errors tend to occur in clusters in exchange rates and stock market returns. Besides, empirical distributions of financial time series and excange rates have tails havier than the normal distribution.

The volatility of currency exchange rates can be considered as an useful measure of uncertainty about the economic environment of a country. There are a vaste literature on modeling and forecasting of exchange rates and of their volatility. The volatility measures the size of the errors appeared in modeling of the currency returns.

In order to model exchange rate returns it is important that all the key characteristics of the data to be captured by the appropriate models. The volatility of the currency returns shows clusters, suggesting the use of GARCH models. In many papers, the main objectiv was to test the hypothesis that the currency exchange rates are asymmetric for negative and positive shocks, using the extensions of the GARCH models.

The ARCH and GARCH models are a class of models with non-constance variances conditioned on the past, which are a linear function on recent past perturbations. These models are used in the analysis of some financial time series, such as stock prices, inflation rates or exchange rates.

The ARCH/GARCH models estimate and test the asset returns process and the volatility process simultaneous. The importance of these models is derived from the difference between conditional and unconditional variances. The unconditional variances are assumed to be time-independent and the conditional variances are assumed to be dependent on past events which are contained in the information set at time t-1.

1.1. The ARCH Model

The ARCH models were introduced by Engle (1982) to explain the volatility of inflation rates. Engle showed that „it is possible to specify a process for the error terms and predict the average size of the error terms when models are fitted to empirical data”.

The econometric models used for to model the volatility of an asset return are referred to as autoregressive conditional heteroscedastic models. The ARCH models are based on an autoregressive representation of the conditional variance. These models allow the variance of the disturbance to modify over time.

The ARCH(q) model can to incorporate two important properties of the returns:

-large (small) changes in returns are likely to be followed by large (small) changes in returns (volatility clustering).

-the unconditional distribution of returns is leptokurtic, having fatter tails than the normal distribution.

The most frequently used exchange rate return series is the first difference of the natural logarithm of the exchange rate and is given by the following equation:

$$r_t = \ln(p_t) - \ln(p_{t-1}) \text{, or } r_t = 100 * [\ln(p_t) - \ln(p_{t-1})] \quad [1]$$

where p_t denotes the exchange rate at period t.

Any ARCH(q) model contains two equations: the conditional mean equation and the conditional variance equation. Both equations must be estimated simultaneous. The conditional mean and the conditional variance will be defined based on a information set available at time t-1.

$$r_t = \mu + \varepsilon_t \text{, } \varepsilon_t \sim N(0, \sigma_t^2) \quad [2]$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 \quad [3]$$

μ is the mean of the dependent variable, σ_t^2 is the conditional variance of the errors at time *t*, ε_{t-1}^2 is the squared error at time $t-1$ and ω is a constant term. σ_t^2 is called the conditional variance, because it is the one-period ahead forecast variance based on past information. The variance equation is an AR(q) model for squared errors. This model estimates the unobservable variance. The lagged terms are called ARCH terms. They can be interpreted as news about volatility or volatility shocks from prior periods. We need of conditions $\omega > 0$ and $\alpha_i \geq 0$, to ensure that the conditional variance is positive.

The errors may be not autocorrelated, but they are not independent. Thus, there will exist the volatility clustering and the fat tails.

1.2. The GARCH(p,q) Model

The GARCH models were introduced by Bollerslev (1986). A GARCH model allows the conditional variance to be dependent upon previous own lags. The conditional disturbance variance can be modeled as:

$$r_t = \mu + \varepsilon_t \text{, } \varepsilon_t \sim N(0, \sigma_t^2) \quad [4]$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \cdots + \beta_p \sigma_{t-p}^2, \text{ with } \omega > 0 \text{ and } \alpha_i \geq 0, \beta_i \geq 0, \quad [5]$$

to ensure that the conditional variance is strictly positive. We can observe that the value of the conditional variance depends on both the past values of the shocks and on the past values of itself. The parameter *p* is the order of the GARCH terms and *q* is the order of the ARCH terms.

The GARCH(1,1) model

The most used heteroscedastic model in financial time series is the GARCH(1,1) model for the asset returns r_t. The conditional variance of r_t is assumed to be a weighted average of a constant variance ω, the past forecast σ_{t-1}^2 and the past squared news ε_{t-1}^2.

The GARCH(1,1) model is given by:

$$r_t = \mu + \varepsilon_t, \ \varepsilon_t \sim N(0, \sigma_t^2) \quad [6]$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2, \quad [7]$$

where ω is the mean, ε_{t-1}^2 is the ARCH term and σ_{t-1}^2 is the GARCH term.

The conditional variance can be written as:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 = \omega + (\alpha + \beta)\sigma_{t-1}^2 + \alpha(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) =$$

$$= \omega + (\alpha + \beta)\sigma_{t-1}^2 + \alpha \sigma_{t-1}^2 (z_{t-1}^2 - 1), \quad [8]$$

where $z_{t-1} = (\varepsilon_{t-1} / \sigma_{t-1})$ are the standardized residuals. The term $(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$ has conditional mean zero and can be interpreted as shock to volatility.

The unconditional variance of the GARCH(1,1) process is given by:

$$\sigma_\varepsilon^2 = \mathrm{var}(\varepsilon_t) = E(\varepsilon_t^2) = \omega / (1 - \alpha - \beta). \quad [9]$$

We can observe that this expression is independent of time. From here, the model is stationary if $\alpha + \beta < 1$.

The parameter α indicates the contributions to conditional variance of the most recent news (shocks). The parameter β indicates the contributions to conditional variance of the recent level of volatility. The sum $\alpha + \beta$ defines the impact of present news in the future volatility. This sum measures the rate at which this effect dies out over time (very slowly). If $\alpha + \beta < 1$ the shocks have a decaying impact on future volatility.

According to Engle and Bollerslev (1986) we define the surprise in the squared innovations as $v_t = (\varepsilon_t^2 - \sigma_t^2)$. The GARCH(1,1) model can be rewritten as an ARMA(1,1) model for the squared errors ε_t^2 :

$$\varepsilon_t^2 = \omega + (\alpha + \beta)\varepsilon_{t-1}^2 + (\varepsilon_t^2 - \sigma_t^2) - \beta(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \qquad [10[$$

$$\varepsilon_t^2 = \omega + (\alpha + \beta)\,\varepsilon_{t-1}^2 + v_t - \beta v_{t-1} \qquad [11]$$

While the errors v_t are uncorrelated over time, they exhibit heteroskedasticity.

This expression of the model can be used to determine the optimal values of *p* and *q* in the GARCH(p,q).

Volatility forecasts

The conditional variance of the returns, given its past values, is the same as the conditional variance of the random errors, given its past values. Thus, the forecasts of σ_t^2 will be forecasts of the future variance of the returns. So, modeling σ_t^2 will give us models and forecasts for r_t as well.

In the GARCH(1,1) model the variance equation can be written, under stationarity condition $\alpha + \beta < 1$, as:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 = \sigma_\varepsilon^2 + \beta(\sigma_{t-1}^2 - \sigma_\varepsilon^2) + \alpha(\varepsilon_{t-1}^2 - \sigma_\varepsilon^2) \qquad [12]$$

Here, the conditional variance and quadratic errors are expressed as deviations from their long-term mean. It can be showed that a stationary GARCH(1,1) model will mean revert to the unconditional variance $\sigma_\varepsilon^2 = \omega/(1 - \alpha - \beta)$, and the volatility can be temporarily above or below the long-run mean.

The component GARCH model allows mean reversion to a varying variance level m_t defined by:

$$\sigma_t^2 - m_t = \alpha(\varepsilon_{t-1}^2 - m_{t-1}) + \beta(\sigma_{t-1}^2 - m_{t-1}) \qquad [13]$$

$$m_t = \omega + \rho(m_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \qquad [14]$$

The transitory component $\sigma_t^2 - m_t$ will converge to zero with powers of $(\alpha + \beta)$. The long-run component m_t will converge to ω with powers of ρ.

The GARCH in Mean

In the mean equation is included some function of conditional variance (usually the standard deviation). This model allows the mean of a series to depend, at least in part, of the conditional variance of the series.

1.3. The EGARCH Model

The Exponential (EGARCH) models were introduced by Nelson (1991).

The GARCH model treats the errors as symmetric. This means that the positive and negative stocks are considered to affect the conditional variance in the same way. The EGARCH model allows to treat the errors as asymmetric, allows good news and bad news to have an asymmetric effect on the conditional variance, allows for different reactions from negative and positive shocks.

In financial markets, a downward movement (depreciation) is always followed by higher volatility. This characteristic of the financial data is called leverage effect. The price movements are negatively correlated with volatility. Volatility is higher after negative shocks than after positive shocks of the same magnitude.

For an EGARCH(1,1) model, the variance equation can be written in the following form:

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad [15]$$

The term $\varepsilon_{t-1} / \sigma_{t-1}$ has the coefficient γ. When the coefficient γ is negative, the positive shocks determine less volatility than the negative shocks, all other conditions being equal.

This model allows the response to the lagged error to be asymmetric, so that a positive regression residual can have a different effect on variance than an equivalent negative residual.

In the case more general, we have the variance equation:

$$\log(\sigma_t^2) = \alpha_0 + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \qquad [16]$$

1.4. The TGARCH models

The Threshold GARCH models were introduced by Glosten, Jagannathan and Runkle (1993). If we consider TGARCH(1,1), the conditional variance equation is given by:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \beta\sigma_{t-1}^2 \qquad [17]$$

where $I_{t-1} = 1$ for past innovations with negative effect (if $\varepsilon_{t-1} < 0$) and $I_{t-1} = 0$, otherwise. In this model, good news ($\varepsilon_{t-1} > 0$) has an impact of α and bad news ($\varepsilon_{t-1} < 0$) has an impact of $(\alpha + \gamma)$. We say that the leverage effect exists, if $\gamma > 0$. If $\gamma \neq 0$, the news impact is asymmetric.

2. Modeling volatility in the RON/EUR exchange rate returns

2.1. General characteristics

The main objective of the empirical study is to investigate the volatility of the returns of daily RON/EUR exchange rate. The data series is the daily RON/EUR exchange rate from 5 january 2009 to 12 octomber 2012. There are 965 observations. We perform the analysis of this return series using various types of GARCH processes.

Most financial studies involve the asset returns, more precisely, log-return series r_t, instead of price series. This is because the returns are a scale-free summary of the asset prices. Also, the return series are easier to handle than price series because of their empirical properties:

- the observations have high-frequency

-the empirical density function has a higher peak around its mean and fatter tails than of a normal distribution

-the daily returns tend to have high excess kurtosis

-the mean of log-return series is close to zero

- $p_t \sim I(1)$ but $r_t \sim I(0)$

-no autocorrelation can be recognized in levels, but in the squared log-returns.

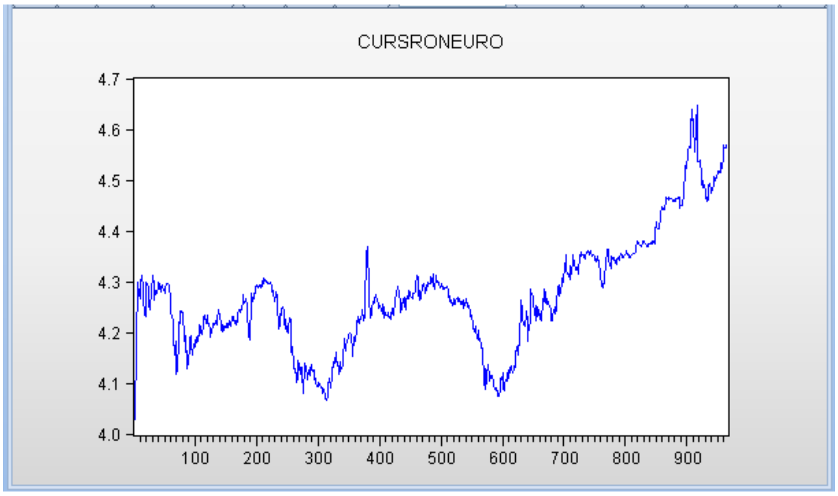

Figure1. The RON/EUR exchange rate series

Figure 1 presents the RON/EUR exchange rate series. An ADF test of stationarity on the sample data showed that the null hypothesis: „Series has a unit root" cannot be rejected for 1% significance level (Table 1).

Augmented Dickey-Fuller Unit Root Test on CURSRONEUR

Null Hypothesis: CURSRONEUR has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=21)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.848810	0.3569
Test critical values:	1% level	-3.436920	
	5% level	-2.864329	
	10% level	-2.568308	

Table 1. ADF test on the RON/EUR exchange rate series

The daily price quotations RON/EUR (p_t) are transformed into series of logarithmic returns, according to $r_t = \ln p_t - \ln p_{t-1}$. Thus r_t denote the RON/EUR exchange rate return at period *t*.

It is easy to check volatility clustering in the returns. The graph of the daily RON/EUR exchange rate returns (Figure 2) shows that this series is not white noise, though its average is very near to zero. The excess returns shows periods of turbulence of the volatility and periods of relative tranquility. This suggests the phenomenon of volatility clustering, or conditional heteroskedasticity, because there are periods of large changes and periods of moderate changes.

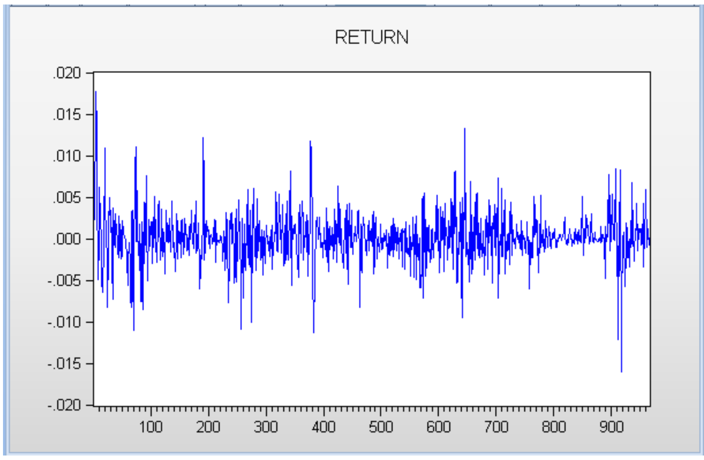

Figure 2. Line graph of the return series

Table 2 presents the descriptive statistics and distribution for the RON/EUR exchange rate return series over the sample period.

Mean	0,000130
Standard Deviation	0,003065
Skewness	0,259258
Kurtosis	7,657592
Jarque-Bera	882,1411
Probability	0,000000

Table 2. Descriptive statistics and distribution for the return series

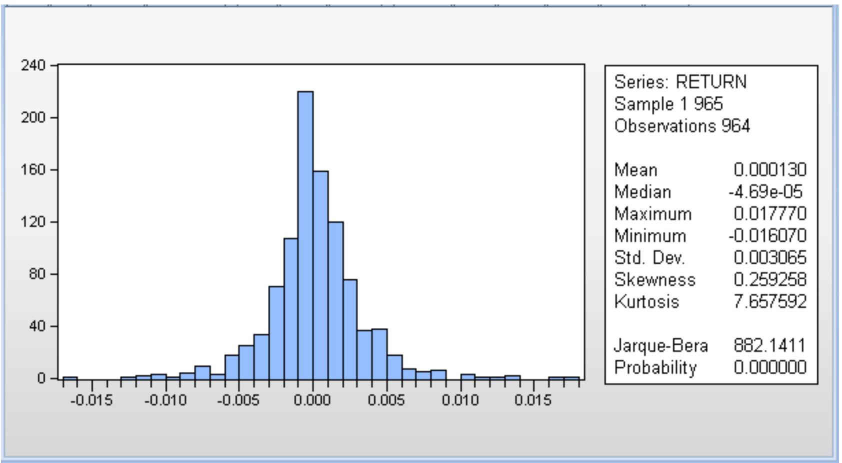

Figure 3. Histogram and Descriptive Statistics

Examining the values of skewness and kurtosis, we can say that the return series is not normally distributed. Because the kurtosis is equal to 7,6576, which excceds 3, the empirical distribution is leptokurtic and it presents fat tails. Both skewness and kurtosis deviate from those of the normal distribution. In addition, for testing whether our series is normally distributed, we computed the Jarque-Bera statistic and the result obtained shows that it is not normally distributed. The return series are checked for correlation in. In Figure 4 we observe the sample ACF and PACF functions of the returns.

The phenomenon known as volatility clustering can be also detected through the application of the Ljung and Box tests for high order of serial correlation in squared returns. We found that we could reject the null hypothesis that the correlations in squared returns are zero.

Results of Heteroscedasticity Test

The presence of ARCH effects in the return series will justify the using of a GARCH model. We tested for ARCH effects in the return series, using ARCH-LM test.

Heteroskedasticity Test: ARCH			
F-statistic	33.00899	Prob. F(1,957)	0.0000
Obs*R-squared	31.97509	Prob. Chi-Square(1)	0.0000

Table 3. The ARCH-LM test in the return series

The ARCH-LM statistic is significant at the 95% confidence level, suggesting the presence of ARCH effects.

An Augmented Dikey-Fuller test of stationarity is performed on the return series. The null hypothesis: „RETURN has a unit root” was rejected for 1% significance level (Table 4).

Augmented Dickey-Fuller Unit Root Test on RETURN

Null Hypothesis: RETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=21)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-24.93790	0.0000
Test critical values:	1% level	-3.436920	
	5% level	-2.864329	
	10% level	-2.568308	

Table 4. The ADF test of stationarity on the return series.

All these results provide justification to continue the analysis of the returns by estimating the conditional variance using a GARCH(1,1) model.

2.2. Estimating the mean equation

It is important to get the mean equation correctly specified before estimating the variance with a GARCH model. Thus, before estimating an GARCH process must to test for the absence of autocorrelation in the residuals. The mean equation can be modeled as a standard regression equation or as an ARMA process with or without explanatory variable. We perform four important stages in building of the volatility model for a return series:

1.We look for the mean equation. For that, it must to build different econometric models for the return series.

2. We use the residuals of the mean equation to test for ARCH effects.

3. If ARCH effects are significant, we specify a volatility model and then we perform a join estimation of the mean and volatility equations.

4. We verify the estimated model.

We builded the mean equation by most models.

In order to choice the best model, for each of the equations we made tests on the residuals and we compared the values of Akaike Information Criterion (AIC), Schwartz Criterion (SC) and Hannan-Quinn Criterion (HQC). The model with the minimum AIC, SC and HQC criteria will be prefered.

An ARMA(1,4) model and an AR(4) model with the second and the third coefficient non-significant were very well. The later is the best model.

The ARMA(1,4) model:

$$r_t = c_1 + c_2 r_{t-1} + c_3 \varepsilon_{t-4} + \varepsilon_t \qquad [18]$$

The AR(4) model:

$$r_t = c_1 + c_2 r_{t-1} + c_3 r_{t-4} + \varepsilon_t \qquad [19]$$

Figure 4 presents the regression output for the model $r_t = c_1 + c_2 r_{t-1} + c_3 r_{t-4} + \varepsilon_t$ for the mean equation.

The residual test is used to check the correct specification of the mean equation. The Ljung-Box test showed the mean equation is correctly specified, because all Ljung-Box Q statistics are not significant. (Figure 5).

We tested for ARCH effects in the residual series in the mean equation, using ARCH-LM test.

Heteroskedasticity Test: ARCH			
F-statistic	0.000492	Prob. F(1,957)	0.9823
Obs*R-squared	0.000493	Prob. Chi-Square(1)	0.9823

Table 5. Testing for ARCH effects in residual series in the mean equation

The ARCH-LM statistic is not significant at the 95% confidence level, suggesting the absence of ARCH effects.

2.3. Estimating the variance equation

Based on the above models which fit very well the sample data, we estimated the GARCH(1,1) model, under a normal distribution of the innovations.

We used the GARCH estimations which are implemented in the EViews econometric software.

One can identify the order of a GARCH model using the correlogram of the squared residuals. This will coincide with ARMA order of the squared residuals of the time series.

Dependent Variable: RETURN
Method: ML - ARCH
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	7.53E-05	7.24E-05	1.040657	0.2980
AR(1)	0.127482	0.034324	3.714057	0.0002
AR(4)	-0.085426	0.031911	-2.676992	0.0074
	Variance Equation			
C	3.37E-07	6.07E-08	5.556833	0.0000
RESID(-1)^2	0.208448	0.031141	6.693760	0.0000
GARCH(-1)	0.767915	0.029704	25.85198	0.0000

Table 6. Estimation output for the GARCH(1,1) model

In the conditional variance equation, all estimated parameters by the GARCH(1,1) models are significant at the 95% confidence level. The coefficients on the lagged squared residual and lagged conditional variance are equal to $\hat{\alpha} \approx 0{,}208$ and $\hat{\beta} \approx 0{,}768$. The sum of both coefficients, $\hat{\alpha}+\hat{\beta}\approx 0{,}976$, is very close to unity. This implies that the shocks to the conditional variance will be persistent.

From the join estimation of the AR(4)-GARCH(1,1) model (Figure 6) we obtained:

$$\hat{\sigma}_t^2 = 0{,}000000337 + 0{,}208448\varepsilon_{t-1}^2 + 0{,}767915\sigma_{t-1}^2 \quad [20]$$

GARCH = 3.37e-07 + 0.208448*RESID(-1)^2 + 0.767915*GARCH(-1) [21]

From the volatility equation, the unconditional variance is:

$$\hat{\sigma}_\varepsilon^2 = \omega/(1-\alpha-\beta) = 0{,}000000337/(1-0{,}208448-0{,}767915) = 1{,}42573E-05 \quad [22]$$

Thus, the model appears to be adequate.

As we can see $\alpha+\beta = 0{,}976363 < 1$, so the process is stable and the level of the long-run variance is $\hat{\sigma}_\varepsilon^2 = 1{,}42573E-05$.

This corresponds to a volatility of 0,00378 or 0,378%.

We used tests based on the estimated standardized residuals to verify the GARCH(1,1) model. These tests suggested that our model is well specified.

The standard model selection criteria (AIC, SC, HQC) are used to determine the orders of the GARCH type models.

2.4. Estimating an EGARCH (1,1) Model

In order to capture asymmetric responses of the time-varying variance to shocks, now we use an EGARCH(1,1) model.

Dependent Variable: RETURN
Method: ML - ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	7.98E-05	6.68E-05	1.193415	0.2327
AR(1)	0.127873	0.033403	3.828193	0.0001
AR(4)	-0.093619	0.030878	-3.031870	0.0024
	Variance Equation			
C(4)	-1.280741	0.196227	-6.526845	0.0000
C(5)	0.367752	0.045721	8.043458	0.0000

C(6)	-0.012856	0.025241	-0.509329	0.6105
C(7)	0.915526	0.014016	65.31780	0.0000

Table 7. Estimation Results of the EGARCH(1,1) with Normal error distribution

We estimated the GARCH and EGARCH models for return series by maximizing the log-likelihood function for each model, assuming that errors follow a normal distribution. The estimated variance equation in EGARCH(1,1) model is:

$$\log(\sigma_t^2) = -1{,}280741 + 0{,}367752\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - 0{,}012856\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + 0{,}915526\log(\sigma_{t-1}^2) \quad [23]$$

The results are presented in Figure 9.

If the relationship between volatility and returns is negative, the asymmetry coefficient γ, corresponding to the $\varepsilon_{t-1}/\sigma_{t-1}$ term, must be negative. We observe the fact that $\gamma = -0{,}012856$, so it has the correct sign, but it is not significant. Thus, an asymmetric effect exists, but is not significant. In the output the first lagged residual indicates the effect of a positive shock, while the second lagged residual indicates the effect of a negative shock.

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6) *RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.44E-05	6.01E-05	0.571959	0.5674
AR(1)	0.095735	0.032719	2.926004	0.0034
AR(4)	-0.068195	0.031132	-2.190497	0.0285
	Variance Equation			
C(4)	-0.774245	0.191963	-4.033304	0.0001
C(5)	0.410974	0.057827	7.106908	0.0000
C(6)	-0.034513	0.035089	-0.983587	0.3253
C(7)	0.959441	0.014403	66.61171	0.0000
T-DIST. DOF	4.168976	0.691053	6.032791	0.0000

Table 8. Estimation Results of EGARCH (1, 1) – Student-t error distribution

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-3.03E-05	5.69E-05	-0.532961	0.5941
AR(1)	0.094879	0.030755	3.085017	0.0020
AR(4)	-0.062695	0.028254	-2.219002	0.0265
	Variance Equation			
C(4)	-1.039083	0.243336	-4.270158	0.0000
C(5)	0.398231	0.065917	6.041440	0.0000
C(6)	-0.044475	0.039817	-1.116986	0.2640
C(7)	0.937246	0.017370	53.95695	0.0000
GED PARAMETER	1.129573	0.071693	15.75571	0.0000

Table 9. Estimation Results of EGARCH (1, 1) – GED error distribution

2.5. *Estimating the TGARCH (1,1) Model*

The TGARCH model is:

$$\sigma_t^2 = 3{,}33E - 07 + 0{,}1916\varepsilon_{t-1}^2 + 0{,}0334\varepsilon_{t-1}^2 I_{t-1} + 0{,}7689\sigma_{t-1}^2 \quad [24]$$

We know that if the asymmetry term γ is positive, the volatility rises more after a large negative shock than a large positive shock of the same size. The asymmetry term $\gamma = 0{,}0334$ has the correct sign, but is not significant.

A comparison of these models will demonstrate that there is not much difference between the results of the estimations. The signs and magnitude of variables across models are very similar. Finally, the EGARCH(1,1) –GED error distribution model seems to fit data the best.

Model	Err.distr.	AIC	SC	HQC	LL	DW
GARCH(1,1)	Normal	-9,070490	-9,040072	-9,058906	4359,835	1,897848
GARCH(1,2)	Normal	-9,071171	-9,035683	-9,057656	4361,162	1,900552
GARCH(2,1)	Normal	-9,069215	-9,033727	-9,055701	4360,223	1,899611
GARCH(2,2)	Normal	-9,069119	-9,028561	-9,053673	4361,177	1,900409
EGARCH(1,1)	Normal	-9,079182	-9,043694	-9,065667	4365,007	1,898965
EGARCH(1,1)	Student-t	-9,158614	-9,118056	-9,143169	4404,135	1,834122

EGARCH(1,1)	GED	-9,162131	-9,121574	-9,146686	4405,823	1,829946
TGARCH(1,1)	Normal	-9,068813	-9,033325	-9,055298	4360,030	1,893680

Table 10. Values of the standard model selection criteria (AIC, SC, HQC)

The best models are used for forecasts (Figures 13,14,15,16).

The estimated conditional variance equation is used in the EGARCH(1,1) models to obtain the news impact curves. These curves can show if the negative shocks have more impact on future volatility than positive shocks of the same magnitude. The news impact curves obtained show a small asymmetry.

Forecast Evaluation

The Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil inequality coefficient are used measures for comparison of the forecasting performances. The best estimated GARCH models in our study are evaluated by using all these measures for evaluating the forecasting performance. The results are shown in Table 11.

Modelul	Err. Distrib.	RMSE	MAE	MAPE	Theil coeff.
GARCH(1,1)	Normal	0,002950	0,002049	107,1136	0,959511
GARCH(2,2)	Normal	0,002949	0,002049	106,6746	0,961033
EGARCH(1,1)	GED	0,002954	0,002046	99,13067	0,974674

Table 11. Forecasting performance of exchange rate returns.

3. Conclusions

The analysis was based on performing and estimating both GARCH and EGARCH models.Each of the models which we used is characterized by a different specification of the conditional variance equation.

The empirical results suggest that, for modeling the volatility of returns, the estimated GARCH models fit the sample data good enough. Because it has been found that residuals of GARCH models fitted to empirical returns exhibit excess kurtosis, we considered EGARCH models where the errors follow a Normal distribution, a Student-t distribution and a generalization error distribution (GED).

Because we observed the fact that the asymmetric effect exists, but is not statistically significant, conclusion may be that a GARCH specification is better suited for this data series.

The conditional volatility of daily excess returns is highly persistent. Negative shocks are associated with an increase in variance and positive shocks are associated with a decrease in variance.

In practice, the GARCH(1,1) process generally seems to work resonably well. The news impact curves obtained, which can show if the negative shocks have more impact on future volatility than positive shocks of the same magnitude, showed a small asymmetry.

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