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MODELING AND FORECASTING EXCHANGE RATE VOLATILITY IN EEC COUNTRIES[1]

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Summary

This main objective of this paper is to examine the properties of the GARCH model and its usefulness in modeling and forecasting the volatility of exchange rate movements in selected EEC countries (Romania, Hungary and Serbia). The daily returns of exchange rates on Hungarian forint (HUF), Romanian lei (ROL) and Serbian dinar (RSD), all against the US dollar are analyzed during the period 03. January 2000 to 15. April 2013 in respect. In order to measure the involved risk, symmetric and asymmetric GARCH models are applied. The accuracy of exchange rate volatility forecast is evaluated through reference to the most commonly used criteria. These include a Mincer-Zarnowitz regression based test, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Diebold and Mariano test (DM test). The results of Mincer-Zarnowitz regression test for selected exchange rate return series showed a clear lack of explanotory power and sub-optimality of the TGARCH model. The results of the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) for the forecasted volatility showed that symmetric model better predict conditional variance of the exchange rate returns, but estimating results indicating that the parameters of forecasts are not satisfactory, i.e. models have little predictive power. Results for Diebold-Mariano test results for Diebold-Mariano test showed that symmetric model outperforming TGRACH forecast in case of Hungarian forint and Serbian dinar sample series, and that only in case of Romania lei TGARCH outperforming the GARCH forecast.

Keywords: Exchange Rate Volatility, GARCH models, EEC countries, Mincer-Zarnowitz regression based test, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Diebold and Mariano test (DM test).

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1 Introduction

Modeling exchange rate volatility has gained a great importance particularly after the collapse of the Bretton Woods agreement when major industrial countries has chosen to shifted towards floating exchange rate from fixed exchange rate regime. Since then, there has been an extensive debate about the topic of exchange rate volatility and its potential influence on welfare, inflation, international trade as well as its role in security valuation, profitability and risk management and investment analysis. Consequently, a number of models have been developed in empirical finance literature to investigate this volatility across different regions and countries (Suliman, 2012).

The traditional measure of volatility as represented by variance and standard deviation is unconditional and does not recognize interesting patterns in asset volatility, e.g., time-varying and clustering properties (Olowe, 2009). Researchers have introduced various models to explain and predict these patterns in volatility. One such approach is represented by time-varying volatility models which were expressed by Engle (1982) as autoregressive conditional heteroskedasticity (ARCH) model and extended by Bollerslev (1986) into generalized ARCH (GARCH) model. These models recognize the difference between the conditional and the unconditional volatility of stochastic process, where the former varies over time while the latter remains constant (McMillan & Thupayagale 2010).

The vulnerability of emerging economies is clearly evidenced by the behavior of their exchange rates, which were very volatile. With the exceptions of those countries that adopt fixed exchange rate, emerging countries generally suffer from large capital flight to any domestic bad signal or systematic risk (Carvalho & Grirbeler 2010).

Although there have been an extensive empirical studies focusing on modeling and estimating exchange rate volatility in developed countries applying different specification little attention has been paid on emerging countries (see, for instance, Balaban 2004, Sandoval 2006, Yoon & Lee 2008, Ng Cheong Vee et.al. 2011, Antonakakis & Darby 2012). To the best of our knowledge, there are not existing studies of EEC countries data that focus on the forecasting performance of models that capture daily exchange rate volatility.

This study examines the properties of the GARCH model and its usefulness in modeling and forecasting the volatility of exchange rate movements in selected EEC countries. The paper applies symmetric GARCH and three asymmetric GARCH models, which are EGARCH, TGARCH and APARCH. The accuracy of exchange rate volatility forecast is evaluated through reference to the most commonly used criteria. These include a Mincer-Zarnowitz regression based test, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Diebold and Mariano test (DM test).

The working paper is structured as follows. Data and methodology is presented in the second chapter. The third chapter presents the results of empirical analysis. Finally, concluding remarks are given in the fourth chapter.

2 Data and Methodology

The dataset consists of the daily returns of exchange rates Hungarian forint (HUF), Romanian lei (RON) and Serbian dinar (RSD) all against the US dollar obtained from national Central bank websites. The choice of these three specific countries was based on the fulfilment several criteria: that they were Eastern European emerging countries, that have not fixed their currency with the US. dollar, our base currency, during the sample period and that daily spot exchange data is available. The study covers the period 03. January 2000 to 15. April 2013 for HUN/USD, 03. January 2003 to 15. April 2013 for RSD/USD and 03. January 2005 to 15. April 2013 for ROL/USD in respect. As in most of empirical finance literature, tha variable to be modelled is percentage daily exchange rate return which is the first difference of the natural logarithm of the exchange rate, i.e. $r_t = (\log P_t - \log P_{t-1}) * 100$.

2.1. GARCH type models

In this paper symmetric GARCH and three asymmetric GARCH models, which are EGARCH, TGARCH and APARCH with variations in their mean equations: AR(1), MA(1), and ARMA(1,1), ARCH in mean is used to analyse the existence of asymmetry in selected EEC exchange markets. The GARCH (p,q) model was first developed by Bollerslev (1986) as a response to severel drawbacks of the ARCH (p) of Engle (1982). When applied to the volatility of financial time series, a GARCH (p,q) process can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{1}$$

Where ε_t is random component with the properties of white noise, size of parameters α and β in the equation determines the observed short-term volatility dynamics obtained from series of returns. The high value of coefficient β indicates that shocks to conditional variance need a long time to disappear, so the volatility is constant. The high value of the coefficient α mean that volatility reacts intensively to changes in the market. In order to have non-explosive process, α + β is restricted to be less than one.

In order to capture asymmetry Nelson (1991) proposed exponential GARCH process or EGARCH for the conditional variance:

$$\log\left(\sigma_t^2\right) = \alpha_0 + \sum_{i=1}^{\infty} \pi_i g\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) \tag{2}$$

Asymmetric relation between returns and volatility change is given as function $g\left(\frac{\varepsilon_t}{\sigma_t}\right)$, which represent linear combination of $\frac{\varepsilon_t}{|\sigma_t|}$ and $\frac{\varepsilon_t}{\sigma_t}$:

$$g(\frac{\varepsilon_t}{\sigma_t}) = \theta\left(\left|\frac{\varepsilon_t}{\sigma_t}\right| - E\left|\frac{\varepsilon_t}{\sigma_t}\right|\right) + \gamma\left(\frac{\varepsilon_t}{\sigma_t}\right) \tag{3}$$

where θ and γ are constants.

First part of equation, $\theta(|z_t| - E|z_t|)$, captures the size effect, while second part, $\gamma(z_t)$, captures the leverage effect.

Zakoian (1994) proposed TGARCH (p,q) model as alternative to EGARCH process, where asymmetry of positive and negative innovations is incorporated in the model by using indicator function:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\left(\alpha_i \varepsilon_{t-i}^2\right) + \sum_{i=1}^{q}\left(\gamma_i d(\varepsilon_{t-i} < 0)\varepsilon_{t-i}^2\right) + \sum_{j=1}^{p}\left(\beta_j \sigma_{t-j}^2\right) \tag{4}$$

where γ_i are parameters that have to be estimated, d(·) denotes the indicator function defined as:

$$d(\varepsilon_{t-i} < 0) = \begin{cases} 1, & \varepsilon_{t-i} < 0 \\ 0 & \varepsilon_{t-i} \geq 0 \end{cases} \tag{5}$$

TGARCH model allows good news, ($\varepsilon_{t-1} > 0$), and bad news, ($\varepsilon_{t-1} < 0$), to have differential effects on the conditional variance. For instance, in the case of TGARCH (1,1) process, good news has an impact of α_i, while bad news has an impact of $\alpha_i + \gamma_i$. For $\gamma_i > 0$, the leverage effect exists.

APARCH (p,q) process, proposed by Ding, Granger and Engle (1993), can be written as:

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i}\right)^\delta + \sum_{j=1}^{p}\left(\beta_j \sigma_{t-j}^\delta\right) \tag{6}$$

Parameter δ in the equation denotes exponent of conditional standard deviation, while parameter γ describes asymmetry effect of good and bad news on conditional volatility. Positive value of γ means that negative shocks from previous period have higher impact on current level of volatility, and otherwise.

2.2. Forecasting evaluation

The accuracy of exchange rate volatility forecast is evaluated through reference to the most commonly used criteria. These include a Mincer-Zarnowitz (1969) regression based test, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Diebold and Mariano (1995) test (DM test).

2.2.1. Mincer-Zarnowitz regression based test

Zarnowitz (1969) regression based test, the true (or realized) volatility is regressed on constant and forecast volatility:

$$\sigma_{realized,\, t+1} = \alpha + \beta\sigma_{forecast,\, t+1} + \varepsilon_t \tag{7}$$

A separate test is conducted for each model to be unbiased, the parameters α and β should be taking the values 0 and 1 respectively. In addition, the R^2 (goodness-of-fit) of the regression is used as a measurement of predictive power of various models concluded. The model with the largest R^2 indicates that the realized volatility can be appropriately explained by the forecast volatility, and therefore has the most powerful forecasting ability.

2.2.2. Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) is average of the absolute forecast error and defines by:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\left(r_t^2 - \sigma_t^2\right)\right| \tag{8}$$

The MAE assigns equal weights to both over and under predictions of volatility. If we compute MAE of the various forecasting models, then we prefer the one with the smallest value of MAE.

2.2.3. Root Mean Square Error (RMSE)

The Root Mean Square Error (RMSE) is defining by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(r_t^2 - \sigma_t^2\right)^2} \tag{9}$$

The RMSE assigns greater weight to large forecast error. If we compute MAE of the various forecasting models, then we prefer the one with the smallest value of MAE.

2.2.4. Diebold and Mariano (DM) test

The Diebold-Mariano test (1995) is a complementary method to compare forecast of two different models in terms of the expected loss observed when using them. This expected loss is calculated following a loss function. Following to the DM test a predefined loss function is specified and express as:

$$d_t = f(e_{t1}) - f(e_{t2}) \tag{10}$$

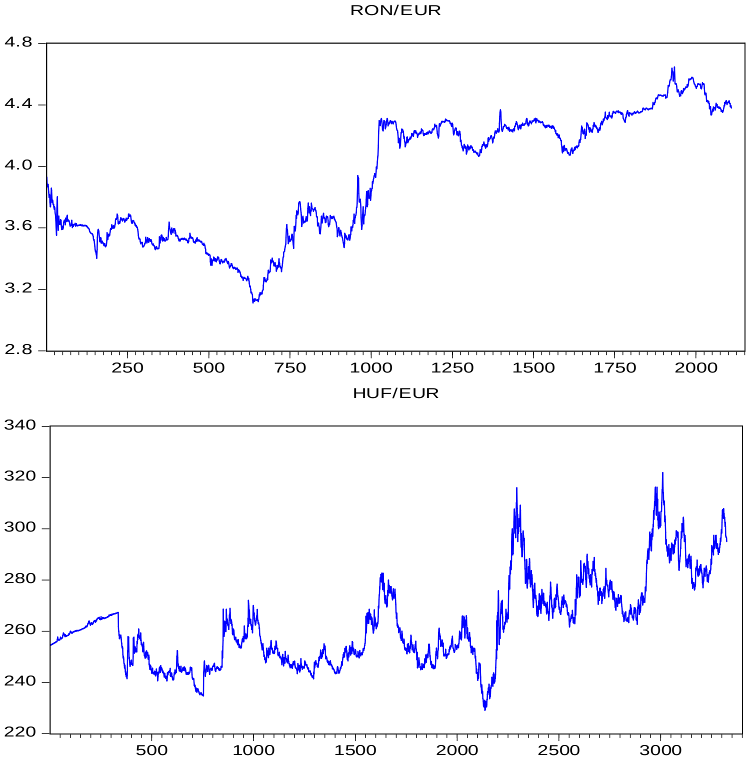
Hence, one can test the null hypothesis $d_t = 0$ of equal forecast accuracy. If the null hypothesis is rejected, then the model with the smallest forecast error is significantly superior to the other model.

3 Results of empirical analysis

3.1. Properties of data

Plots of the data are presented in Figure 1. As may be seen, in the period of crisis it can be noticed a significant depreciation of the exchange rates of Serbia, Hungary and Romania, and that in the previous period, there are shifting periods of appreciation and depreciation of the observed exchange rates.

FIGURE 1: DAILY EXCHANGE RATES VS US DOLLAR



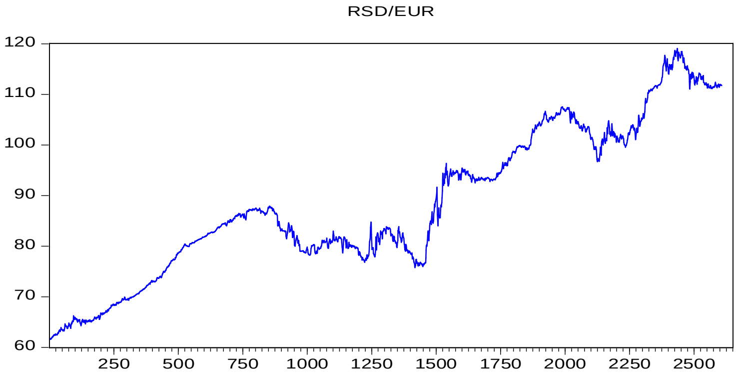


Table 1 shows the results of unit root test for daily exchange rate returns series. The Augmented Dickey-Fuller test and Phillips-Perron test statistics for all exchange rate returns are highly significant, i.e. the values are less then their critical values at 1%, 5% and 10% level, thereby suggesting the rejection of null hypothesis of the presence of unit root in the return series. Therefore, it is appropiate to examine the return volatility using the original level of the series, i.e. there is no need to difference the data.

TABLE 1: UNIT ROOT TEST OF THE DAILY EXCHANGE RATES

	Augmented Dickey-Fuller test				Phillips-Perron test			
	Statistic	Critical values			Statistic	Critical values		
		1% level	5% level	10% level		1% level	5% level	10% level
RON	-43.098 (0.00)	-3.433	-2.862	-2.567	-43.018 (0.00)	-3.433	-2.862	-2.567
HUF	-59.159 (0.00)	-3.432	-2.862	-2.567	-59.176 (0.00)	-3.432	-2.862	-2.567
RSD	-46.495 (0.00)	-3.432	-2.862	-2.567	-46.535 (0.00)	-3.432	-2.862	-2.567

Source: Author's calculations. Note: P values of corresponding test statistics are given in parentheses.

Notice in Figure 2 that, unlike the level, the returns are stationary (outcome confirmed by ADF and PP test). Additionaly, one can observe that the assumption of constante variance is not valide for all series. Volatility clustering is clearly visible in all cases. The efect of the global financial crisis, although this represent relatively a short period in the entire sample, also appear to have strong influence on the exchange rate variability in observed countries.

The quantiles of an empirical distribution are plotted against the quantiles of a normal distribution. From the Figure 3 it is clear that QQ plot is not linear and that empirical distribution differs from the hypothesized normal distribution. The plot poses the characteristic S-shape indicating that there is no significant skewnees, but the tails are havier than a normal distribition (Andersen et.al., 2000).

FIGURE 2: VOLATILITY OF DAILY EXCHANGE RATE RETURNS

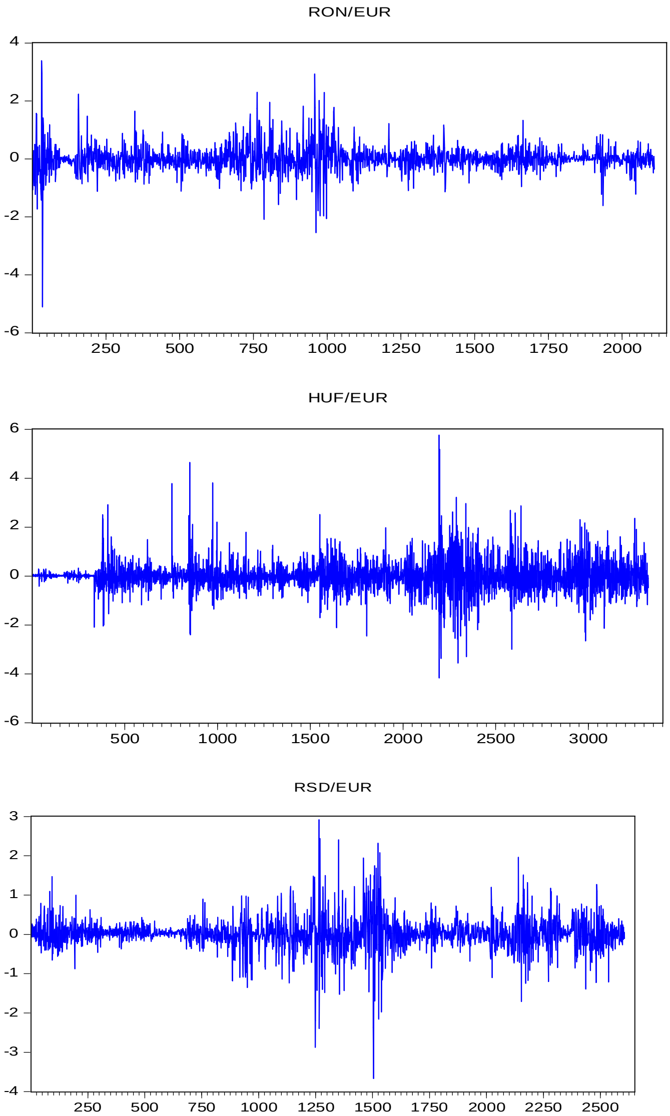


FIGURE 3: QUANTILE-QUANTILE PLOTS OF DAILY EXCHANGE RATE RETURNS

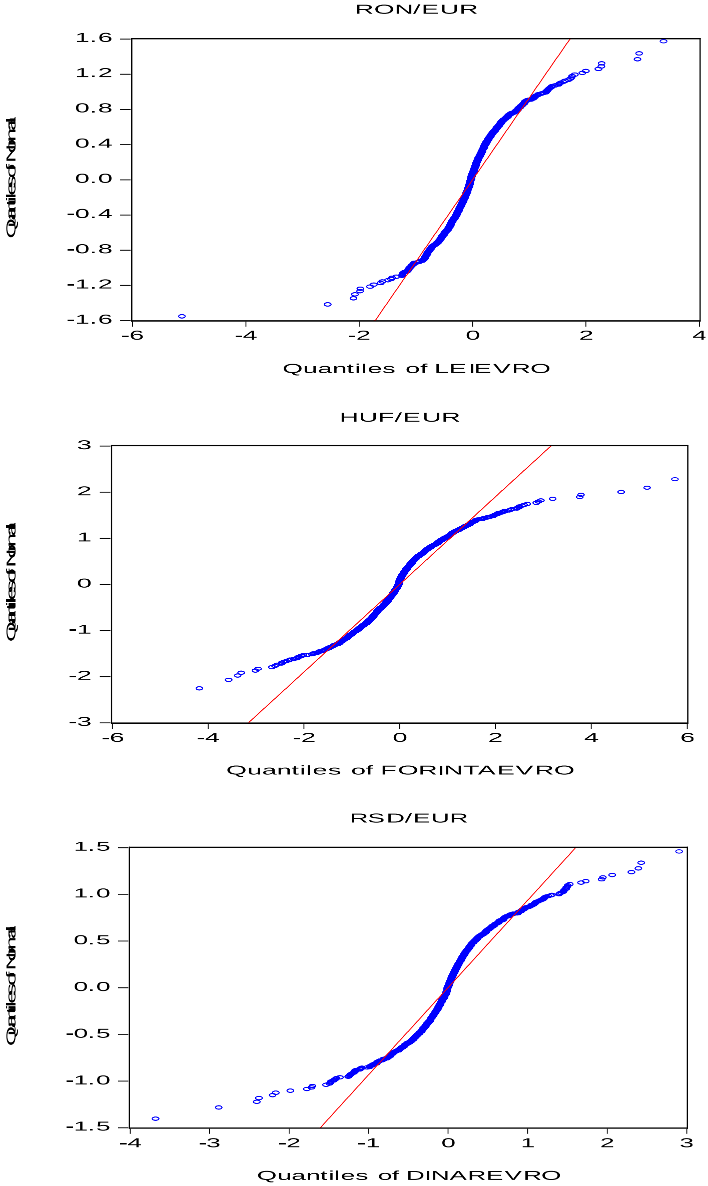


Table 2 indicates that the daily exchange rate returns are not normally distributed. In most cases a modest skewness is evident; kurtosis is in all cases greater than 3 and the Jarque-Bera statistics are highly significant. Positively skewed distribution are reported for all observed daily exchange rate ruturns which indicate depreciation of the currency. The coefficient of excess kurtosis is in all cases much greater than 3 indicating the distribution of the returns is leptokurtic, which means that the distribution has fatter tails. The largest coefficient of excess kurtosis is reported for Romanian leu and highlights that these exchange rates account for larger deviations in their returns. The results confirm the presence of fat tails, which suggest that the assumption of a normal distribution is not satisfied. Consinstent with the results on skeweness and kurtosis, the Jarque-Bera normality test strongly rejects the null hypothesis that returns are normally distributed. Inference is therefore based on Student's t distribution which is have been shown to perform better in theses circumstences.

Table 2 offer strong evidence of ARCH effects in the exchange rate returns series. Formally, using the ARCH-LM test we reject the null hypothesis of no ARCH effect in the residuals, similarly there is evidence of significant serial correlation in the standardised squared returns on the basis of Box-Ljung statistics at every lag tested.

TABLE 2: DESCRIPTIVE STATISTICS OF DAILY EXCHANGE RATE RETURNS

	Skewness	Kurtosis	JB	$Q^2(10)$	$Q^2(30)$	ARCH-LM (10)	ARCH-LM (30)
RON	0.300	6.474	1091.89 (0.00)	576.12 (0.00)	1323.8 (0.00)	274.63 (0.00)	361.94 (0.00)
HUF	0.297	6.379	1629.63 (0.00)	1321.0 (0.00)	2380.8 (0.00)	494.25 (0.00)	566.85 (0.00)
RSD	0.151	5.472	673.73 (0.00)	745.84 (0.00)	2067.0 (0.00)	332.54 (0.00)	479.23(0.00)

Source: Author's calculations. Note: P values of coresponding test statistics are given in parentheses.

3.2. Estimation results

Bearing in mind that Box-Ljung autocorrelation test for squared standardized residuals and ARCH/LM tests indicate presence of ARCH effects, we estimate models of conditional autoregressive heteroscedasticity (GARCH type models). Model selection was done according to modified Akaike criteria. Model parameters are calculated using maximum likelihood estimation method. Maximum likelihood estimates of the parameters are obtained by numerical maximization of the log-likelihood function using the BHHH algorithm.

Conducted empirical test indicate that the return distributions are not characterized by normality. Due to excess kurtosis of daily financial return distributions, estimates based with assumption that residuals follow normal distribution has its drawbacks.

3.2.1. Estimation results of GARCH(1,1) model

The estimation results of GARCH(1,1) model in Table 3 show that AR or MA component in the mean equation is not significant except in case of Serbia where AR component is significant but estimated value of the autoregression parameter is very small (0.071). As far as conditional variance equation concern, the first three coefficients constant (c), ARCH (α) and GARCH term (β) are statistically significant at the 5% level and with expected sign for all return series. The statistical significance of the coefficient α shows the presence of volatility clustering in GARCH (1,1) model for all series. The value of coefficient β shows magnitude variance on the current variance and shows magnitude of volatility clustering. The value of β coefficient is highly significant which shows that persistence volatility clustering prevails in in all exchange rate return series. This volatility clustering reveals that once volatility persists it takes long time to become smooth. Also the significance of both α and β indicates that news about volatility from the previous periods have an explanatory power on current volatility.

TABLE 3: PARAMETER ESTIMATES OF GARCH MODEL WITH T DISTRIBUTION OF THE STANDARDIZED RESIDUALS

	RON	HUF	RSD
Mean equation			
Constant	-0.025 (0.08)	-0.030 (0.03)	
AR(1)			0.071 (0.00)
MA(1)			
Volatility equation			
c	0.009 (0.00)	0.010 (0.00)	0.009 (0.00)
α	0.064 (0.00)	0.051 (0.00)	0.050 (0.00)
β	0.922 (0.00)	0.938 (0.00)	0.933 (0.00)

Source: Author's calculations

3.2.2. Estimation results of asymmetric GARCH models

The estimation results of asymmetric GARCH(1,1) models in Table 4 show that AR or MA component in the mean equation is not significant except in case of Serbia where AR component is significant but estimated value of the autoregression parameter is very small (0.071). Table 4 show that TGARCH (1,1) model is the best fit of asymmetric models for all series. The asymmetrical TGARCH (1,1) results in Table 4 indicate that all estimated coefficients are statistically significant at 5% level. The parameter for asymmetric volatility response (γ) is negative and significant for all cases, indicating an asymmetric response for positive returns in the conditional variance equation. This result reflects the condition that volatility tends to rise in response to positive spikes and fall in response to negative spikes.

TABLE 4: PARAMETER ESTIMATES OF THE ASYMMETRIC GARCH MODEL WITH T DISTRIBUTION OF THE STANDARDIZED RESIDUALS

	RON/USD	HUF/USD	RSD/USD
Mean equation			
Constant			
AR(1)			0.007 (0.00)
MA(1)			
Volatility equation			
c	0.013 (0.00)	0.012 (0.00)	0.009 (0.00)
α	0.092 (0.00)	0.071 (0.00)	0.063 (0.00)
β	0.907 (0.00)	0.941 (0.00)	0.932 (0.00)
θ			
γ	-0.039 (0.04)	-0.053 (0.00)	-0.023 (0.07)

Source: Author's calculations

3.2.3. Diagnostic checks

Table 5 shows the result of the diagnostic checks on estimated symmetric and asymmetric GARCH models. Results of Ljung-Box Q -test statistics of the standardized residuals for the remaining serial correlation in mean equation show that autocorrelation for the standardized residuals are statistically insignificant at 5% level for all lags and models confirming the absence of serial correlation in the standardized residuals. This shows that the mean are well specified in all models. The Ljung-Box Q^2-statistics of the squared standardized residuals are in almost any case all insignificant at 5% level for all lags and models confirming the absence of ARCH in the variance equation. The ARCH-LM statistics for all models showed that the standardized residuals did not exhibit additional ARCH effect. These results suggest that the variance equations are well specified in all models. The Jarque-Bera statistics still show that the standardized residuals are not normally distributed. In sum, all models are adequate for forecasting purposes.

TABLE 5. AUTOCORRELATION OF STANDARDIZED RESIDUALS, AUTOCORRELATION OF SQUERED STANDARDIZED RESIDUALS AND ARCH LM TEST

	GARCH model			TGARCH model		
	RON	HUF	RSD	RON	HUF	RSD
Ljung-Box Q-Statistics						
Q(2)	5.43 (0.06)	0.06 (0.96)	1.79 (0.18)	5.16 (0.07)	0.04 (0.97)	1.84 (0.17)
Q(15)	21.92 (0.11)	12.79 (0.61)	13.97 (0.49)	21.46 (0.12)	14.32 (0.50)	14.04 (0.44)
Ljung-Box Q^2-Statistics						
Q2(2)	4.57 (0.10)	5.40 (0.06)	2.63 (0.10)	3.45 (0.17)	3.00 (0.21)	2.69 (0.10)
Q2(15)	15.69 (0.40)	23.46	15.35	13.94	21.22	15.20

		(0.07)	(0.35)	(0.53)	(0.13)	(0.36)
ARCH-LM						
ARCH (2)	4.73 (0.09)	5.60	2.71	3.55	3.14	2.72
		(0.06)	(0.25)	(0.16)	(0.20)	(0.25)
ARCH (15)	16.40 (0.35)	23.38	14.98	14.43	20.73	14.89
		(0.07)	(0.45)	(0.49)	(0.14)	(0.45)
JB	109.75 (0.00)	171.69	45.00	113.29	181.19	41.08
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Source: Author's calculations

3.3. Forecast evaluation

We chose only models in table 4 and 5, best symmetric and the best asymmetric of each country to compare its predictability of exchange rate volatility within the sample.

Table 6. shows the Mean Absolute Error (MAE) and the Root Mean Squere Error (RMSE) for the forecasted volatility. Note that symmetric model better predict conditional variance of the exchange rate return in all cases. However, estimating results indicating poor prediction power of estimating models since the values of MAE and RMSE for both models are large and ranges of 0.223 up to 0.406 for MAE and 0.236 to 0.406 for RMSE. Based on obtained results we can conclude that the parameters of forecasts are not satisfactory, i.e. models have little predictive power.

TABLE 6: RESULTS FOR 30-DAY FORECAST MAE AND RMSE

	MAE		RMSE	
	GARCH	TGARCH	GARCH	TGARCH
RON	0.376	0.401	0.376	0.401
HUF	0.376	0.406	0.376	0.406
RSD	0.225	0.223	0.236	0.236

Source: Author's calculations

Table 7 present the results of Mincer-Zarnowitz regression test for selected exchange rate return series. All the regression against the sample forecast of the GARCH variance, showed a clear lack of explanotory power and sub-optimality in the model. The coefficient β was always around 1 therefore, the null hypothesis ($c = 0$ and $\beta = 1$) was always rejected. The measure of predictability R^2 is very low and ranges between 0.121 to 0.143. These results indicate that the goodness-of-fit is extremly poor for TGARCH model which is unbiased.

TABLE 7: MINCER-ZARNOWITZ REGRESION

RON

Variable	Coefficient	Std. Error	t-Statistic	Prob.	c=0 and β=1
C	0.033884	0.052362	0.647104	0.5176	YES
HTGARCH	0.940699	0.054997	17.10469	0.0000	NO

R^2=0.121977

HUF

Variable	Coefficient	Std. Error	t-Statistic	Prob.	c=0 and β=1
C	-0.005853	0.058360	-0.100286	0.9201	YES
HTGARCH	1.013297	0.043040	23.54318	0.0000	NO

R^2=0.143067

RSD

Variable	Coefficient	Std. Error	t-Statistic	Prob.	c=0 and β=1
C	-0.041244	0.039950	-1.032390	0.3020	YES
HTGARCH	1.086913	0.057077	19.04284	0.0000	NO

R^2=0.122319

Source: Author's calculations

Finally, table 8 show the application of Diebold-Mariano test. The main objective of the test is to distinguish between two forecasts in terms of the minimizition of certain loss function. Results of Diebold-Mariano test do not confirme the results obtained before. Note that symmetric model outperforming TGRACH forecast in case of Hungarian forint and Serbian dinar. Only in case of Romania lei TGARCH outperforming the GARCH forecast.

TABLE 8: DIEBOLD-MARIANO TEST

RON

Dependent variable: d(garch-tgarch)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.161245	0.050938	3.165536	0.0016

HUF

Dependent variable: d(garch-tgarch)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000740	0.001065	0.694443	0.4875

RSD

Dependent variable: d(garch-tgarch)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.91E-05	2.39E-05	-0.799252	0.4242

Source: Author's calculations

4 Conclusion

This main objective of this paper is to examine the properties of the GARCH model and its usefulness in modeling and forecasting the volatility of exchange rate movements in selected EEC countries. The paper applies symmetric GARCH and three asymmetric GARCH models, which are EGARCH, TGARCH and APARCH with variations in their mean equations: AR(1), MA(1), and ARMA(1,1), ARCH in mean, that capture most stylized facts about exchange rate returns such as volatility clustering and leverage effect. The accuracy of exchange rate volatility forecast is evaluated through reference to the most commonly used criteria. These include a Mincer-Zarnowitz regression based test, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Diebold and Mariano test (DM test).

The dataset consists of the daily returns of exchange rates Hungarian forint (HUF), Romanian lei (RON) and Serbian dinar (RSD) all against the US dollar obtained from national Central bank websites. The choice of these three specific countries was based on the fulfilment several criteria: that they were Eastern Europea emerging countries, that have not fixed their currency with the US. dollar, our base currency, during the sample period and that daily spot exchange data is available. The study covers the period 03. January 2000 to 15. April 2013 for HUN/USD, 03. January 2003 to 15. April 2013 for RSD/USD and 03. January 2005 to 15. April 2013 for ROL/USD in respect.

The criterion of model selection for each of the four GARCH type models based on in-sample diagnostic test. Theses include the modified Akaike criteria on both raw (Q) and squared (Q^2) standardized residuals, Engle's LM ARCH test for the presence of ARCH effects in the series. Under the Student's t distribution, the model with the minimum value of modified Akaike criteria and which pass the Q-test and LM ARCH test were adopted.

We chosed only best symmetric and the best asymmetric model of each country to compare its predictability of exchange rate volatility within the sample. The results of Mincer-Zarnowitz regression test for selected exchange rate return series showed a clear lack of explanotory power and sub-optimality of the TGARCH model. The results of the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) for the forecasted volatility showed that symmetric model better predict conditional variance of the exchange rate returns, but estimating results indicating that the parameters of forecasts are not satisfactory, i.e. models have little predictive power.

Finally, results for Diebold-Mariano test, our strongest test, showed that symmetric model outperforming TGRACH forecast in case of Hungarian forint and Serbian dinar sample series, and that only in case of Romania lei TGARCH outperforming the GARCH forecast.

Our results sugests that analyst has to be aware of the posible effect of asymmetry when modeling volatility of an emerging exchange rate series, but on average results of forecasting will not obtain a statistically significant better forecast when shifting from a symmetric to an asymmetric GARCH model.

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