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Volatility analysis of the Romanian exchange rate

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Abstract

Volatility has been traditionally analysed from the perspective of economic cycles and only recently as an autonomous process with a major influence on different macroeconomic approaches. Volatility is associated with risk in the sense that it offers a measure of possible variations of economic variables and the increased volatility of the markets can trigger economic crises as it can be seen in economic history. The paper intends to analyse the volatility of the leu/euro exchange rate taken into account the influence of the volatility of other currencies and other fundamental macroeconomic variables. The analysis is based on specific methods for high frequency time series. The database is comprised of daily time series for the period 05.01.2000-31.08.2013. The application of different ARCH-GARCH models indicate that the volatility of the leu/euro exchange rate follows an ARCH process, that there is a high asymmetry in the evaluation of information regarding the evolution of the exchange rate and that the exchange rate returns are correlated with volatility.

Keywords:

1. Introduction

The recent economic-financial crisis has been contributing, among others, to the increase of uncertainty level in the business environment by altering the currency supply and demand in Romania and foreign countries. An

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efficient measure of the uncertainty level is the exchange rate volatility, a high level of it pointing to frequent changes in currency demand, which is determined by capital inputs and outputs. In this context, the forecast of exchange rate becomes difficult and the investors are more reluctant to invest in a business environment mastered by uncertainty. A large number of risk management models are using volatility as a lead indicator to exchange rate risk.

In principal, the fundamental factors influencing the exchange rate evolution, starting from theoretical fundaments (commercial balance, currency demand or nominal incomes) can be found in Messe and Rogoff study, 1983.

There is a clear difference between short term and long term exchange rate forecast, the research papers pointing out that the structural models perform better in average for long term forecasts while unvaried predictions based on white noise (Cheung, Chin and Pasqual, 2002) perform better in average for short term forecasts. In addition, the Tambakis and Van Royen, 2002 study pointed out that the GARCH type models are of a superior prediction accuracy to the white noise based models, while the models based on uncovered interest rate demonstrated a prediction accuracy superior to the others, taking into consideration that the study considered developed country currency (Euro Region, German Mark, English Pound versus UD Dollar) both short and long term. In the context of volatility clustering of the exchange rate it is recommended the usage of GARCH models (Griebeler, 2010), the performance being at a superior level with TARCH and EGARCH models as well as for the TARCH-M models including conditional volatility as an conditional mean regression. The results of those models were not superior while applied in the emergent countries comparing to the developed countries. In countries like Brasil and UK the linear GARCH models gave better results while in other countries the performance level was higher with EGARCH models. An interesting paper regarding the exchange rate volatility in CEE countries treat this topic from the short and long term perspective by applied a Component GARCH model before the impact of financial crises from 2008. The paper proves a lower magnitude of the long term correlation between euro and CEE currency as compare to the transitory component and a great volatility of a transitory component (Cristina MorarTriandafil and all, 2011).Anton, 2012 applied the TGARCH model in order to forecast the volatility of BET indices and Acatrinei, Adrian and Nicu, 2013, applied a DCC-GARCH model to estimate the risk of the capital market in Romania

The paper has four distinct parts: the first is dedicated to the existing literature, the second is dedicated to the methodology presentation; the third part analyzes the data series and the four part present the results and comments of the model.

2. The methodology

Mandelbrot,1963 and Fama,1965 pointed out that the exchange rate data series are, generally, characterized by conditional heteroscedasticity, asymmetry and clustered volatility, fact that implies the need to cancel the normal distribution hypothesis, a different approach being needed to modelling those data series.In this context a number of models have been developed that, according to Pacelli, 2012, can be structured in two main categories:

- *structural models* based on an error dispersion function like autoregressive models with conditional heteroscedasticity (ARCH) developed by Engle, 1982 and generalized by Bollersley, 1986 as the general autoregressive model with conditional heteroscedasticity(GARCH), extended in two directions: *univariate GARCH models* and *multivariate GARCH models of VECH type*;
- *black box forecasting models* like neural network models (ANN) or genetic algorithm models, fuzzymodels used in pricing series analysis with nonlinear dynamics or series that don't have a white noise pattern.

Starting with Bollerslev, 1986, a the new type of generalized model class was developed in which the variance can be written as:

$$\sigma 2= \omega+\beta 0\sigma t\text{-}12 + \beta 1\sigma t\text{-}22+.......+ \beta k\sigma t\text{-}k2 +\alpha 0\epsilon t2 + \alpha 1\epsilon t\text{-}12+.......+ \alpha m\epsilon t\text{-}m2 \qquad (1)$$

The simplest form of GARCH model is:

$$\sigma 2= \omega+\beta\sigma t\text{-}12+ \alpha\epsilon t2 \qquad (2)$$

Where: $\alpha+\beta<1$, the variance process shows the mean reversion process towards unconditional expectations $\sigma 2$, $\omega/(1\text{-}\alpha\text{-}\beta)$. This means that the prognosis of future volatility equals to unconditional means $\sigma 2$, $\omega/(1\text{-}\alpha\text{-}\beta)$.

The GARCH models have been utilized to predict US dollar exchange rate by Bailliesand Bollerslev,1989,

1991andeuro exchange rateby Neely 1999, the accuracy of this model being improved by measuring volatility during the daytime, as demonstrated by Andersen andBollerslev, 1998. Neely and Weller, 2001 estimated daily volatility for German Mark and Japanese Yen using a GARCH(1,1) model in comparison with the Risk Metrics model, concluding that these models have a superior level of forecasting error absolute mean comparing to the prediction models based on genetic algorithms.

A large survey of the multivariate GARCH model was presented by Bouwens, Laurent and Kombouts, 2006 in order to show if the volatility of a market influence the volatility of another market. The relation between the volatilities and co-volatilities of different market was studies in the work of Kearney and Patton 2000, Karolyi,1995. An interesting list of the utility of multivariate GARCH model was offered by Tse 2000, p.108:"model the changing variance structure in an exchange rate regime (Bollerslev, 1990), calculate the optimal debt portfolio in multiple currencies (Kroner and Claessens,1991), evaluate the multiperiod hedge ratios of currency futures (Lien and Luo, 1994), examine the international transmission of stock returns and volatility (Karolyi, 1995) and estimate the optimal hedge ratio for stock index futures (Park and Switzer, 1995)". The modelling with multivariate GARCH model are some advantage as the intuition of the GARCH models, there also some disadvantage that was overpass by others class of GARCH models as BEKK (named after Baba, Engle, Kraft and Kroner) model which ensure a solution of the condition of a positive–definite conditional variance matrix in the process of optimisation, but induce the problems of interpretation of parameters. Derivate from the VECH –GARCH model, the GARCH model can be used unrestricted for a small number of variables, or restricted either as a diagonal or a scalar. In the case of diagonal restricted model, the covariance of the GARCH (1, 1) model can be written as:

$$\Sigma_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + B\Sigma_{t-1}B \quad (3)$$

Where C is a triangular matrix of small dimension NxN, and the matrices A and B are the matrices of parameters by NxN, dimension without restriction. The constant term matrices could be decompose in two matrices C and C' in order to be sure that the conditional covariance matrices should be positive defined.

In the case of a great number of parameter could be possible the convergence problems. In order to solve that problem, a restricted diagonal BEKK GARCH (1,1) model is used, as in equation (4).

$$\Sigma_t = CC' + \widetilde{A}\varepsilon_{t-1}\varepsilon'_{t-1}\widetilde{A}' + \widetilde{B}\Sigma_{t-1}\widetilde{B}' \quad (4)$$

Where the matrix $\widetilde{A}$ și $\widetilde{B}$ is the matrix of NxN parameter dimension, and *C* is a triangular small dimension matrix of NxN dimension.

The conditional variance could be written as:

$$\sigma_{ij,t} = \widetilde{c}_{ij} + a_i a_j \varepsilon_{i,t-1}\varepsilon_{j,t-1} + b_i b_j \sigma_{ij,t-1} \quad (5)$$

In the case of a large number of parameter could be used a scalar BEKK GARCH model, with a conditional variance:

$$\Sigma_t = CC' + a^2\varepsilon_{t-1}\varepsilon'_{t-1} + b^2\Sigma_{t-1} \quad (6)$$

Where *a* and*b* are scalar parameters.

If we desired to present the co-movement of the exchange rate from different countries, we can analyse the conditional covariance from the pairs of the exchange rate as in equation 7.

$$\rho_{xy,t} = \frac{\sigma_{xy,t}}{\sqrt{\sigma_{xx,t}\sigma_{yy,t}}} \quad (7)$$

In the diagonal BEKK model the parameters of the covariance equation are the product of parameters of the variance equation and scalar BEKK is the most restricted version of the diagonal BEKK model.

3. Data and empirical properties

The data used in our paper covers the period 05.01.2000-30.08.2013. It was used daily date from EUROSTAT database for nominal exchange rate RON per Euro (symbol leu), for exchange rate USA_dollar per Euro (symbol us_dolar),for exchange rate zloty per Euro (symbol zloty) and for exchange rate Crown per Euro (symbol koruna_cz). There were constituted a continue data set of 3394 data that was converted for the needs of fitting the model to a logarithmic return series noted as dlog(leu), dlog(koruna_cz), dlog(us_dolar) and dlog(zloty), based on the formula:

$$dlogX = \ln(X_t/X_{t-1}) \qquad (8)$$

The X is the name of variable.

The statistical analysis shows the presence of heteroscedasticity, a great volatility, the clustering of volatility and the cluster tend to occur simultaneously as we can see from the figure 1.
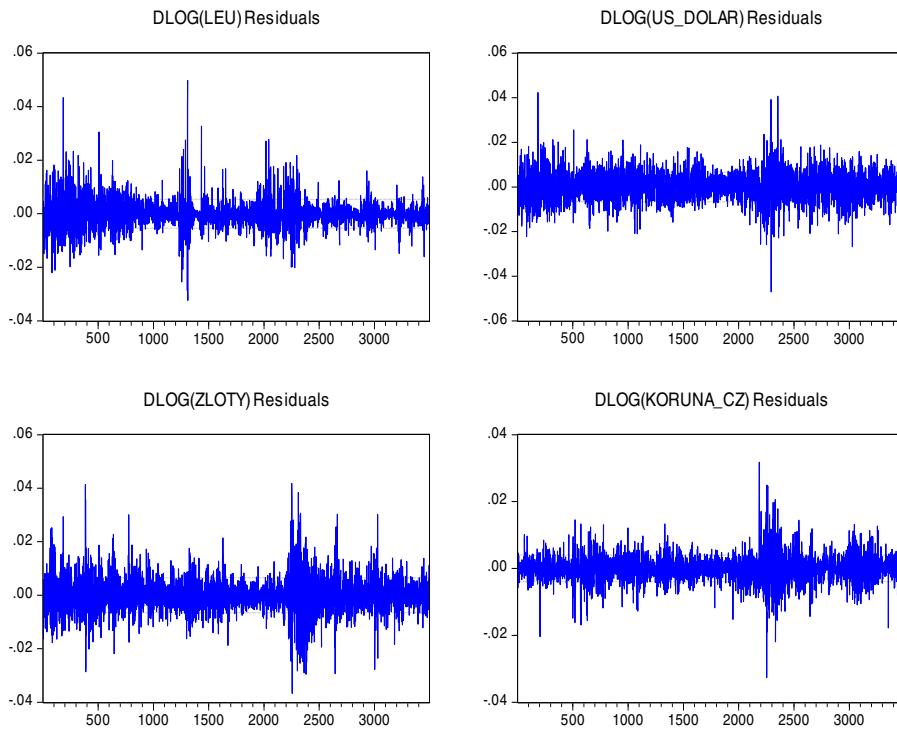

Fig.1 Corresponding Logarithmic Return of the Exchange Rate

We can also see that the mean is close to zero and the return, generally, exhibit the positive skewness and excess kurtosis.

Table 1 descriptive statistics

	dlog(leu)	dlog(us_dolar)	dlog(zloty)	dlog(koruna_cz)
Mean	0.000243	6.99E-05	4.03E-08	0.000243
Median	0.000000	0.000226	-0.000256	-0.000115
Maximum	0.050005	0.042041	0.041636	0.031650
Minimum	-0.032105	-0.047354	-0.036798	-0.032745
Std. Dev.	0.005375	0.006615	0.006532	0.003953
Skewness	0.834003	-0.008267	0.454379	0.080697
Kurtosis	10.75801	5.467410	7.631075	8.998235
Jarque-Bera	9169.846	886.6213	3243.462	5243.209
Probability	0.000000	0.000000	0.000000	0.000000
Sum	0.848103	0.244141	0.000141	-0.344985
Sum Sq. Dev	0.100926	0.152890	0.149089	0.054607
Observations	3495	3495	3495	3495

The kurtosisis above the three meaning the existence of the excess kurtosis; the skewness is positive for three of the variable, only for the dlog (us_dolar) is negative and the high level of the e Jarque–Bera test indicate the non-normality of the distributions. All that information motivates an application of the multivariate GARCH model.

4. Empirical results and discussion

Using a scalar BEKK GARCH (1,1) model the convergence was achieved after 15 iteration. We chose the Bollerslev-Wooldridge robust standard errors & covariance.The parameters are presented in the table 2.

Table 2 The transformed variance coefficients

	Coefficients	Std. Error	z-Statistic	Probabilities
Diagonal BEKK model with scalar				
M	3.88E-08	8.42E-09	4.604833	0.0000
A1(1,1)	0.293226	0.010964	26.74452	0.0000
A1(2,2)	0.238870	0.010921	21.87289	0.0000
A1(3,3)	0.252065	0.010620	23.73545	0.0000
A1(4,4)	0.153300	0.009091	16.86235	0.0000
B1(1,1)	0.962256	0.002181	441.1178	0.0000
B1(2,2)	0.974328	0.002017	483.0937	0.0000
B1(3,3)	0.971979	0.001900	511.6042	0.0000
B1(4,4)	0.987669	0.001195	826.7314	0.0000

Note: A stands for ARCH coefficient and B represents the GARCH coefficient, and M is a scalar.

The figure 2 presents the conditional correlation. The correlations from scalar BEKK model are strongly positive in the case of leu/zloty and leu/koruna_cz exchange rate and less correlated in the case of leu/us_dolar, which is obvious from figure 2.
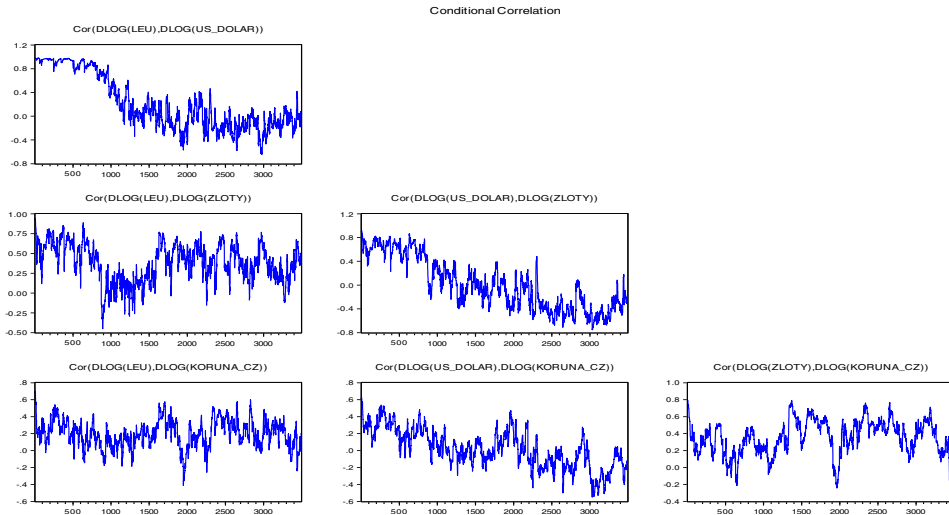
Fig. 2 Conditional correlation

Regarding the conditional variance we can see the high impact of the shock which do not occurred simultaneously as result of the different factors that impact the dynamics of the exchange rates.
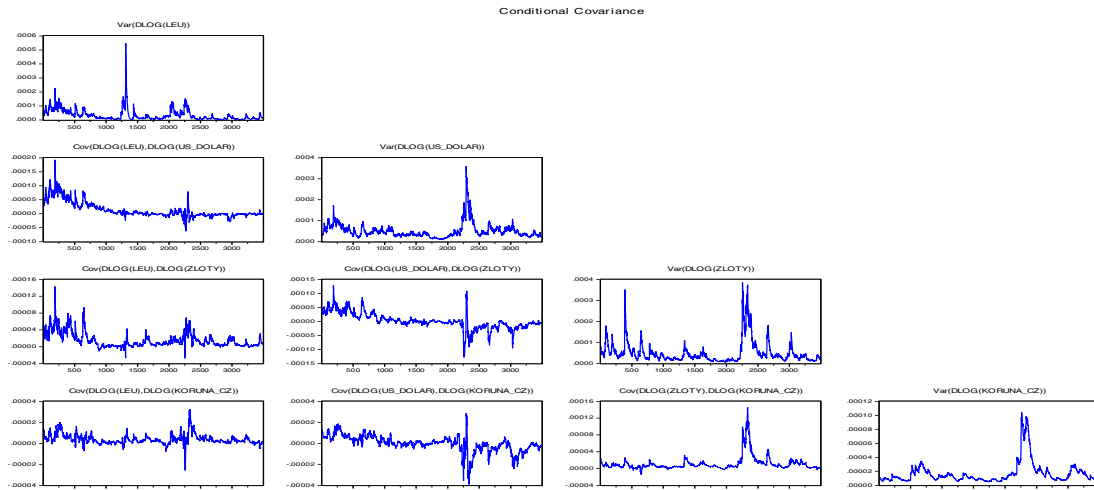

Fig 3. The Conditional Variance and covariance of the model

As we see in the fig. 3 different from the behaviour of Us_dollar, zloty and Koruna_cz that react very strongly to the financial crisis of 2008, the leu behaves rather different, the impact of crisis was less as compared to the other exchange rates and the high shock was linked to the change of the reference implicit basket(75% euro and 25% dollar and later 100% euro) and the flexibility of the exchanger rate regime which led to the great unpredictability as result of the reduction of NBR interventions.

The diagonal BEKK model with scalar restriction offered a way to model co-movement of the exchange rate currency of four countries and the result show that the covariance correlation is higher in the case of the European market (Romanian, Polish and Czech Republic). The lack of normal distribution is still a problem even if it was used the Bollerslev-Wooldridge robust standard errors & covariance, because the estimator is consistent but not asymptotically efficient.

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