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An empirical analysis of Euro Hungarian Forint exchange rate volatility using GARCH

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The paper aims to analyse and forecast Euro Hungarian Forint exchange rate volatility with the use of generalised autoregressive conditional heteroscedasticity GARCH-type models over the period from September 30, 2010 to January 02, 2017. This model is the extension of the ARCH process with various features to explain the obvious characteristics of financial time series such as asymmetric and leverage effect. In applying EUR/HUF with this model, we performed both estimation and forecast.

Keywords: Volatility, GARCH, EURHUF, Volatility forecast

1. Introduction

In recent years, the study of the volatility of a market variable measuring uncertainty about the future value of the variable has played a prominent part in monitoring and assessing potential losses. Quantitative methods measuring the volatility of the Euro Hungarian Forint exchange rate have received the most attention because of its role in determining the price of securities and risk management. Typically, a series of financial indices have different movements in a certain period. This means that the variance of the range of financial indicators changes over time. The Euro Hungarian Forint exchange rate is one of the most crucial markets by market capitalization and liquidity in central Europe.

According to Econotimes (2016): "the momentum of Hungarian economic growth is likely to slow in 2016, following a strong expansion of 3 percent last year. The Hungarian economy will be impacted by the warning of the regional auto industry boom, pausing of EU fund inflow in 2016 before picking up again in 2017 and the risk to the German economy from developments in China. The end of easing cycle is expected to result in a stable forint in the coming quarters. However, the currency is likely to face slight upward pressure from Brexit related uncertainties. The EUR/HUF is likely to trade at 322 by the end of 2016, stated Commerzbank. Persistent low inflation is expected to renew rate cut expectations in the coming year. Such a development, combined with an expected deceleration of the GDP growth in 2016, is expected to exert upward pressure on the EUR/HUF pair by the end of 2016". Therefore, the investigation of the volatility of the Euro Hungarian Forint exchange rate is timely indeed.

As Bantwa (2017) mentions, for most investors, the prevailing market turmoil and a lack of clarity on where it is headed are a cause for concern. The majority of investors in markets are mainly concerned about uncertainty in gaining expected returns as well as volatility in returns. Diebold et al. (2003) provide a framework for integrating high-frequency intraday data into the measurement, modeling, and forecasting of daily and lower frequency return volatilities and return distributions. Use of realized volatility computed from high-frequency intraday returns permits the use of traditional time series methods for modeling and calculating.

Banerjee and Kumar (2011) focus on comparing the performance of conditional volatility model GARCH and Volatility Index in predicting underlying volatility of the NIFTY 50 index. Using high-frequency data, the underlying volatility of the NIFTY50 index is captured. Several approaches to predicting realized volatility are considered.

Wiphatthananananthakul and Songsak (2010) estimated ARMA-GARCH, EGARCH, GJR and PGARCH models for the Thailand Volatility Index (TVIX), and drew comparisons in forecasting between the models. GARCH model has become a key tool in the analysis of time series data, particularly in financial applications. This model is especially useful when the goal of the study is to analyze and forecast volatility according to Degiannakis (2004). With the generation of GARCH models, it is able to reproduce another, very vital stylised fact, which is volatility clustering; that is, big shocks are followed by big shocks.

In this paper, we applied GARCH model to estimate, compute and forecast EUR/HUF volatility. Nevertheless, it should be pointed out that several empirical studies have already examined the impact of asymmetries on the performance of GARCH models. The recent survey by Poon and Granger (2003) provides, among other things, an interesting and extensive synopsis of these. Indeed, different conclusions have been drawn from these studies. The rest of the paper proceeds as follows: the concept of volatility and GARCH model are described in the next section, and the final section will discuss results and offer a conclusion.

2. Theoretical Background, Concept and Definitions

2.1. Definition and Concept of Volatility

Hull (2015, p. 201) states that “the volatility σ of a variable is defined as the standard deviation of the return provided by the variable per unit of time when the return is expressed using continuous compounding. When volatility is used for option pricing, the unit of time is usually one year, so that volatility is the standard deviation of the continuously compounded return per year. However, when volatility is used for risk management, the unit of time is usually one day, so that volatility is the standard deviation of the continuously compounded return per day.”

In general, $\sigma\sqrt{T}$ is equal to the standard deviation of $ln\left(\frac{S_T}{S_0}\right)$ where S_T is the value of the market variable at time T and S_0 is its value today. The expression $ln\left(\frac{S_T}{S_0}\right)$ equals the total return earned in time T expressed with continuous compounding. If σ is per day, T is measured in days, if σ is per year, T is measured in years".

The volatility of EUR/HUF variable is estimated using historical data. The returns of EUR/HUF at time t are calculated as follows:

$R_i = ln\frac{p_i}{p_{i-1}}, i = \overline{1,n}$

where p_i and p_{i-1} are the prices of EUR/HUF at time t and $t-1$, respectively. The usual estimates s of the standard deviation of R_i is given by

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(R_\mathrm{i} - \bar{R})^2}$$

where $\bar{R}$ is the mean of R_i.

As explained above, the standard deviation of R_i is $\sigma\sqrt{T}$ where σ is the volatility of the EUR/HUF.

The variable s is, therefore, an estimate of $\sigma\sqrt{T}$. It follows that σ itself can be estimated as $\hat{\sigma}$, where $\hat{\sigma} = \frac{s}{\sqrt{T}}$

The standard error of this estimate can be shown to be approximately $\frac{\hat{\sigma}}{\sqrt{2n}}$. T is measured in days, the volatility that is calculated is daily volatility.

2.2. GARCH Model

The GARCH model by Bollerslev (1986) imposes important limitations, not to capture a positive or negative sign of u_t, as both positive and negative shocks have the same impact on the conditional variance, h_t, as follows

$u_t = \eta_t\sqrt{\sigma_t}$
$\sigma_t^2 = \omega + \sum_{i=1}^{p}\alpha_i u_{t-1}^2 + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2$
where $\omega > 0$, $\alpha_i \geq 0$, for $i = \overline{1,p}$

and $\beta_j \geq 0$ for $j = \overline{1,q}$ are sufficient to ensure that the conditional variance, σ_t is non-negative. For the GARCH process to be defined, it is required that $\omega > 0$. Additionally, a univariate GARCH(1,1) model is known as ARCH(∞) model (Engle 1982) as an infinite expansion in u_{t-1}^2. α represents the ARCH effect and β represents the GARCH effect. GARCH(1,1) model, σ_t^2 is calculated from a long-run average variance rate, V_L, as well as from σ_{t-1} and u_{t-1}. The equation for GARCH(1,1) is

$$\sigma_t^2 = \gamma V_L + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2$$

where γ is the weight assigned to V_L, α is the weight assigned to u_{t-1}^2 and β is the weight assigned to σ_{t-1}^2. Since the weights must sum to one, we have $\gamma + \alpha + \beta = 1$.

2.3. Volatility forecasting

There is a broad and relatively new theoretical approach that attempts to compare the accuracies of different models for conducting out-of-sample volatility forecasts. Akgiray (1989) observed the GARCH model to be superior to ARCH, exponentially weighted, moving average and historical mean models for forecasting monthly US stock index volatility.

West and Cho (1995) indicated that the apparent superiority of GARCH used one-step-ahead forecasts of dollar exchange rate volatility, although for longer horizons, the model behaves no better than its counterparts. Specifically, Day and Lewis (1992) examined GARCH and EGARCH models in depth and considered their out-of-sample forecasting performance for predicting the volatility of stock index.

Arowolo (2013) concluded that the Optimal values of p and q in a GARCH(p,q) model depends on location, the types of the data and model order selected techniques being used. The model that Day and Lewis (1992) employed was a so called a 'plain vanilla' GARCH(1,1):

$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$

when they applied the properties of linear GARCH model for daily closing stocks prices of Zenith bank PlC on the Nigerian stocks exchange.

2.4. Data Description

The data for our empirical investigation consists of the EUR/HUF index transaction prices obtained from Bloomberg, accounted by the Department of Finance, Corvinus University of Budapest, the sample period being from September 30, 2010 to January 02, 2017 which constitutes a total of $n = 1654$ trading days. For the estimation, we use the daily returns of EUR/HUF to estimate GARCH(1,1) by using Eview 7.0 software.

3. Results

3.1. Descriptive Statistics

The descriptive statistics of daily logarithmic returns of the EUR/HUF is given in Table 1. The average return of EUR/HUF is positive. A variable has a normal distribution if its skewness statistic equals zero and its kurtosis statistic is 3, but the return of EUR/HUF has a positive skewness and high kurtosis, suggesting the presence of fat tails and a non-symmetric series. Additionally, as we can see, the Jarque-Bera normality test rejects the null hypothesis of normality for the sample, this means we can draw a conclusion that the return of EUR/HUF is not normally distributed. The relatively large kurtosis indicates non-normality, and that the distribution of returns is leptokurtic.

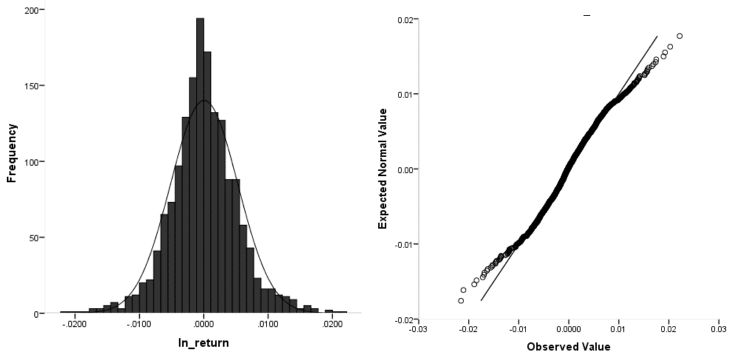
Table 1 Descriptive statistics of EUR/HUF Returns

Mean	**Std. Dev**	**Skewness**	**Kurtosis**	**Max**	**Min**
0.000068	0.005235	0.087168	4.479947	0.022156	-0.021550
Jarque-Bera			153.0389		
Probability			0.000000		

Source: own construction

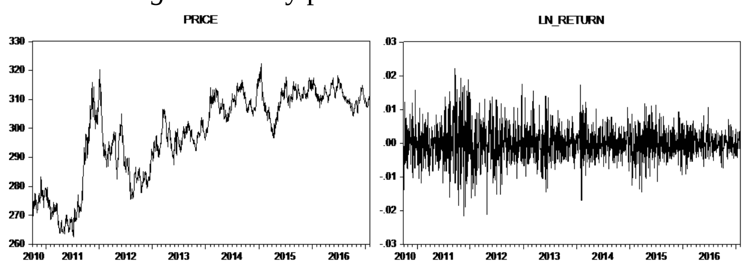
Figure 1 depicts the histogram of daily logarithmic return for EUR/HUF. From this histogram, it appears that EUR/HUF returns have a higher peak than the normal distribution. In general, Q-Q plot is used to identify the distribution of the sample in the study, it compares the distribution with the normal distribution and indicates that EUR/HUF returns deviate from the normal distribution.

Figure 1 Histogram and Q-Q Plot of Daily Logarithmic EURHUF returns



Source: own construction

Figure 2 Daily price and EURHUF returns



Source: own construction

Figure 2 presents the plot of price and EUR/HUF returns. This indicates some circumstances where EUR/HUF returns fluctuate.

The unit root tests for EUR/HUF returns are summarized in Table 2. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were used to test the null hypothesis of a unit root against the alternative hypothesis of stationarity. The tests have large negative values of statistics in all cases at levels such that the return variable rejects the null hypothesis at the 1 per cent significance level, and therefore, the returns are stationary.

Table 2 Unit root test for Returns of EUR/HUF

Test	**None**	**Constant**	**Const & Trend**
Phillips-Perron	-43.07319	-43.07511	-43.06830
ADF	-42.82135	-42.81734	-42.80833

Source: own construction

3.2. Estimation

Table 3 represents the ARCH and GARCH effects from statistically significance at 1 per cent level of α and β. It shows that the long-run coefficients are all statistically significant in the variance equation. The coefficient of α appears to show the presence of volatility clustering in the models. Conditional volatility for the models tends to rise (fall) when the absolute value of the standardized residuals is larger (smaller). The coefficients of β (a determinant of the degree of persistence) for all models are less than 1, showing persistent volatility.

Table 3 GARCH on Returns of EUR/HUF

	GARCH				
	Mean Equation			**Variance Equation**	
	Coefficient	z-statistics		Coefficient	z-statistics
Constant	0.000022	0.205460	ω	0.000000163	2.468227 (0.0136)
Mean			α	0.054850	6.529890 (0.0000)
			β	0.938494	101.6264 (0.0000)

Source: own construction

GARCH(1,1) model is estimated from daily data as follows

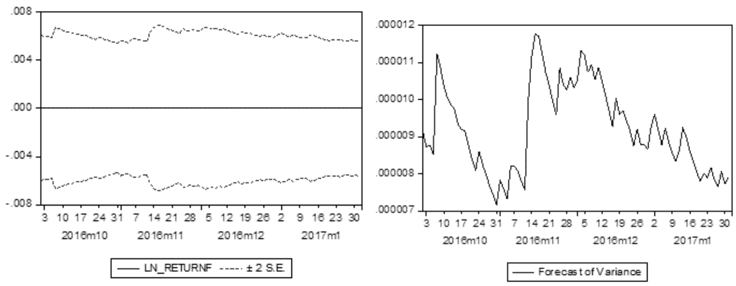
$$\sigma_t^2 = 0.000000163 + 0.054850u_{t-1}^2 + 0.938494\sigma_{t-1}^2$$

Since $\gamma = 1 - \alpha - \beta$, it follows that $\gamma = 0.000656$ and, since $\omega = \gamma V_L$, we have $V_L = 0.000024489$. In other words, the long-run average variance per day implied by the model is 0.000024489. This corresponds to a volatility of $\sqrt{0.000024489} = 0.004948$ or 0.49%, per day.

3.3. Forecasting Results Using GARCH (1,1) Model

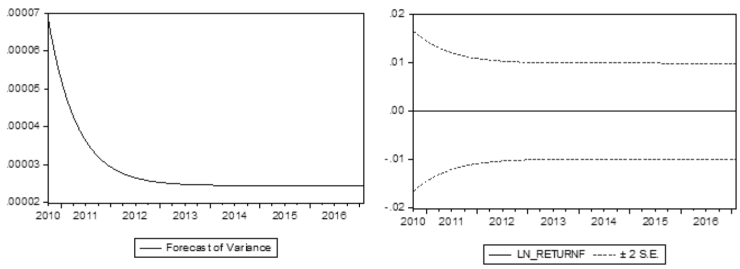
The selected model $\sigma_t^2 = 0.000000163 + 0.054850u_{t-1}^2 + 0.938494\sigma_{t-1}^2$ has been tested for diagnostic checking and there is no doubt of its accuracy for forecasting based on residual tests. We can use our model to predict the future volatility value. Figures 3 and 4 show the forecast value. It can be seen that the forecast of the conditional variance indicates a gradual decrease in the volatility of the stock returns. The dynamic forecasts show a completely flat forecast structure for the mean, while at the end of the in-sample estimation period, the value of the conditional variance was at a historically lower level relative to its unconditional average. Therefore, the forecast converges upon their long term mean value from below as the forecast horizon decreases. Notice also that there are no $\pm$ 2-standard error band confidence intervals for the conditional variance forecasts. It is evidence for static forecasts that the variance forecasts gradually fall over the out–of sample period, indeed they show much more volatility than for the dynamic forecasts (see Figure 3 and Figure 4).

Figure 3 Static forecasts of the conditional variance



Source: own construction

Figure 4 Dynamic forecasts of the conditional variance



Source: own construction

4. Conclusion

This paper estimates the volatility of the Euro Hungarian Forint exchange rate returns using GARCH model from the seemingly complicated volatility formula established by Bollerslev (1986). The results of statistical properties obtained supported the claim that the financial data are leptokurtic. The GARCH model was identified to be the most appropriate for the time-varying volatility of the data. The results from an empirical analysis based on the Euro Hungarian Forint exchange rate showed the volatility is 0.49% per day. Additionally, the results of forecasting conditional variance indicate a gradual decrease in the volatility of the stock returns. This is in contrast to the findings of Wiphatthananthakul and Songsak (2010).

References

Akgiray, V. (1989): Conditional heteroskedasticity in time series of stock returns: Evidence and forecasts. *Journal of Business*, 62, 1, 55–80.

Arowolo, W. B. (2013): Predicting stock prices returns using GARCH Model. *The International Journal of Engineering and Science*, 2, 5, 32–37.

Banerjee, A. – Kumar, R. (2011): Realized volatility and India VIX, IIM Calcutta. *Working Paper Series*, No. 688.

Bantwa, A. (2017): A study on India volatility index (VIX) and its performance as risk management tool in Indian Stock Market. *Indian Journal of Research*, 6, 1, 248–251.

Bollerslev, T. (1986): Generalized autoregressive heteroskedasticity. *Journal of Econometrics*, 31, 3, 307–327.

Day, T. E. – Lewis, C. M. (1992): Stock market volatility and the information content of stock index options. *Journal of Econometrics*, 52, 1-2, 267–87.

Degiannakis, S. (2004): Forecasting realized intraday volatility and value at Risk: Evidence from a fractional integrated asymmetric Power ARCH Skewed t model. *Applied Financial Economics*, 14, 18, 1333–1342.

Diebold F. X. – Andersen T. – Bollerslev T. – Labys, P. (2003): Modelling and forecasting realized volatility. *Econometrica*, 71, 2, 529–626.

Econotimes (2016): Hungarian economic growth to slow in 2016; EUR/HUF likely to face mild upward pressure. Retrieved from http://www.econotimes.com/Hungarian-economic-growth-to-slow-in-2016-EUR-HUF-likely-to-face-mild-upward-pressure-232142. Date of access: 6 July 2016.

Hull, J. C. (2015): *Risk management and financial institutions*. Hoboken, NJ: John Wiley & Sons, Inc.

Poon, S. H. – Granger, C. W. J. (2003): Forecasting volatility in financial markets: A review. *Journal of Economic Literature*, 41, 2, 478–539.

West, K. D. – Cho, D. (1995): The predictive ability of several models of exchange rate volatility. *Journal of Econometrics*, 69, 2, 367–391.

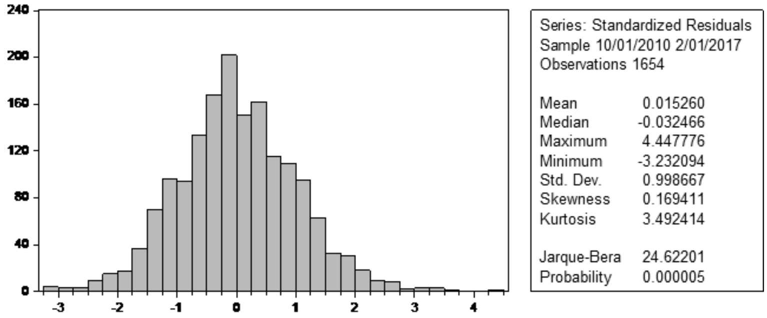
Wiphatthananthakul, C. – Songsak, S. (2010): The comparison among ARMA-GARCH, -EGARCH, -GJR, and -PGARCH models on Thailand Volatility Index. *The Thailand Econometrics Society*, 2, 2, 140–148.

APPENDIX

The residual test

Date: 03/17/17 Time: 14:57
Sample: 10/01/2010 2/01/2017
Included observations: 1654

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.027	-0.027	1.2230	0.269
| |	| |	2	-0.008	-0.008	1.3206	0.517
| |	| |	3	-0.063	-0.064	7.9102	0.048
| |	| |	4	-0.016	-0.019	8.3203	0.081
| |	| |	5	-0.008	-0.010	8.4150	0.135
| |	| |	6	0.017	0.013	8.9164	0.178
| |	| |	7	-0.013	-0.015	9.2126	0.238
| |	| |	8	0.034	0.032	11.090	0.197
| |	| |	9	-0.011	-0.008	11.307	0.255
| |	| |	10	-0.033	-0.035	13.170	0.214
| |	| |	11	0.017	0.019	13.632	0.254
| |	| |	12	-0.011	-0.012	13.846	0.311
| |	| |	13	0.017	0.013	14.318	0.352
| |	| |	14	0.017	0.018	14.816	0.391
| |	| |	15	-0.043	-0.042	17.849	0.271
| |	| |	16	-0.063	-0.065	24.568	0.078
| |	| |	17	-0.036	-0.040	26.762	0.062
| |	| |	18	0.013	0.008	27.066	0.078
| |	| |	19	0.011	-0.000	27.286	0.098
| |	| |	20	-0.012	-0.019	27.511	0.121
| |	| |	21	0.019	0.020	28.145	0.136
| |	| |	22	-0.009	-0.009	28.274	0.167
| |	| |	23	-0.031	-0.030	29.922	0.152
| |	| |	24	0.018	0.021	30.476	0.169
| |	| |	25	-0.039	-0.041	32.992	0.131
| |	| |	26	-0.024	-0.034	33.958	0.136
| |	| |	27	0.014	0.010	34.281	0.158
| |	| |	28	-0.024	-0.026	35.216	0.164
| |	| |	29	0.010	0.005	35.399	0.192
| |	| |	30	0.000	0.000	35.399	0.228
| |	| |	31	0.009	0.006	35.523	0.264
| |	| |	32	0.003	-0.008	35.537	0.305
| |	| |	33	0.037	0.034	37.850	0.257
| |	| |	34	0.000	0.008	37.850	0.298
| |	| |	35	0.019	0.013	38.475	0.315
| |	| |	36	-0.045	-0.037	41.892	0.230



Heteroskedasticity Test: ARCH

F-statistic	0.815876	Prob. F(1,1651)		0.3665
Obs*R-squared	0.816461	Prob. Chi-Square(1)		0.3662
Test Equation:				
Dependent Variable: WGT_RESID^2				
Method: Least Squares				
Date: 03/17/17 Time: 14:59				
Sample (adjusted): 10/04/2010 2/01/2017				
Included observations: 1653 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.974711	0.045924	21.22463	0.0000
WGT_RESID^2(-1)	0.022225	0.024606	0.903258	0.3665
R-squared	0.000494	Mean dependent var		0.996877
Adjusted R-squared	-0.000111	S.D. dependent var		1.578091
S.E. of regression	1.578178	Akaike info criterion		3.751629
Sum squared resid	4112.059	Schwarz criterion		3.758175
Log likelihood	-3098.721	Hannan-Quinn criter.		3.754056
F-statistic	0.815876	Durbin-Watson stat		2.000105
Prob(F-statistic)	0.366521			