MODELING EXCHANGE RATE VOLATILITIES IN CROATIA

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Abstract

Modeling and forecasting exchange rate volatility has important implications in a range of areas in macroeconomics and finance. A number of models have been developed in empirical finance literature to investigate this volatility across different regions and countries. Well known and frequently applied models to estimate exchange rate volatility are the autoregressive conditional heteroscedastic (ARCH) model advanced by Engle (1982) and the generalized (GARCH) model developed independently by Bollerslev (1986) and Taylor (1986). This paper examines the performance of several ARCH models for the EUR and USD against the HRK on daily data sets within the time period from 1997 to 2015. Evaluating the models through standard information criteria showed that the GARCH (2,1) is the best fitted model for the EUR/HRK and the GARCH (1,1) for the USD/HRK daily return volatility. In accordance to the estimated models there is no empirical evidence that negative and positive shocks imply a different next period volatility of the daily EUR/HRK as well as the USD/HRK exchange rate return.

Keywords: GARCH model, heteroscedasticity, exchange rate volatility, Croatia

1. Introduction

There has been an extensive debate about the topic of exchange rate volatility and its potential influence on welfare, inflation, international trade and degree of external sector competitiveness of the economy and also its role in security valuation, investment analysis, profitability and risk management etc. It is argued that there is a positive impact of exchange rate stability on economic growth as exchange rate stability contributes to more trade, capital inflows and macroeconomic stability (Schnabl, 2008). Schnabl (2008) confirmed this through panel estimations on the impact of the exchange rate volatility on economic growth in 41 EMU periphery countries. He found a robust negative relationship between the exchange rate volatility and economic growth. Concerning the impact of the exchange rate volatility on trade, for a long time it has been in the center of debate on the optimality of the choice of exchange rate regimes. Proponents of fixed rates argue that since the establishment of the floating regime, exchange rates have become volatile. With the move to a flexible exchange rate system in 1973, nominal exchange rate volatility has exhibited remarkable persistence (Vilasuso, 2002). Exchange rate deters industries from engaging in international trade and compromises progress in trade negotiations (Côté, 1994). Proponents of flexible exchange rate regimes argue that exchange rates are mainly driven by fundamentals and those changes in fundamentals would require similar, but more abrupt movements in fixed parities (Côté, 1994). A flexible exchange rate need not be an instable exchange rate and if this is the case it is primarily due to underlying instability in the economic conditions (Friedman, 1953). The exchange rate instability is a manifestation of economic instability and underlying systematic volatility cannot be reduced by the regime, only channeled to one locus or another (Flood and Rose, 1999). It is hard to believe that the post-1973 floating era has been so much more volatile from a macroeconomic perspective than the pre-1973 fixed period. In the approximations, countries with fixed exchange rates have less volatile exchange rates than floating countries but macroeconomics that are equally volatile (Flood and Rose, 1999). According to Borghuis and Kuijs (2004) who analyzed the role of the exchange rate for the Czech Republic, Hungary, Poland, Slovakia and Slovenia, the exchange rate in the aforementioned countries has served as much or more as an unhelpful propagator of monetary and financial shocks than as a useful absorber of real shocks. Countries with more stable rates suffer the greatest reduction in the transaction value of the domestic currency when their exchange rates vary, due to their small size and dependence on trade (Bayoumi and Eichengreen, 1998).

To our best knowledge the EUR/HRK and the USD/HRK exchange rate behavior pattern has not been the subject of previous research using GARCH models. Conclusively, the main aim of this paper is to determine the EUR/HRK as well as the USD/HRK exchange rate behavior pattern using GARCH models and make the comparison between them. So, the research hypothesis states: the EUR/HRK and the USD/HRK exchange rate volatilities can be determined using GARCH models.

The rest of the paper is organized as follows: section 2 briefly summarizes existing literature on the modeling of exchange rate volatilities. Section 3 provides relevant facts on the exchange rate in Croatia and its fluctuation constraints. Section 4 shows the research data, while Section 5 the methodology. Section 6 gives the empirical results and discussion. The final section provides an overview of the main findings of the research.

2. *Brief exchange rate volatilities modeling literature overview*

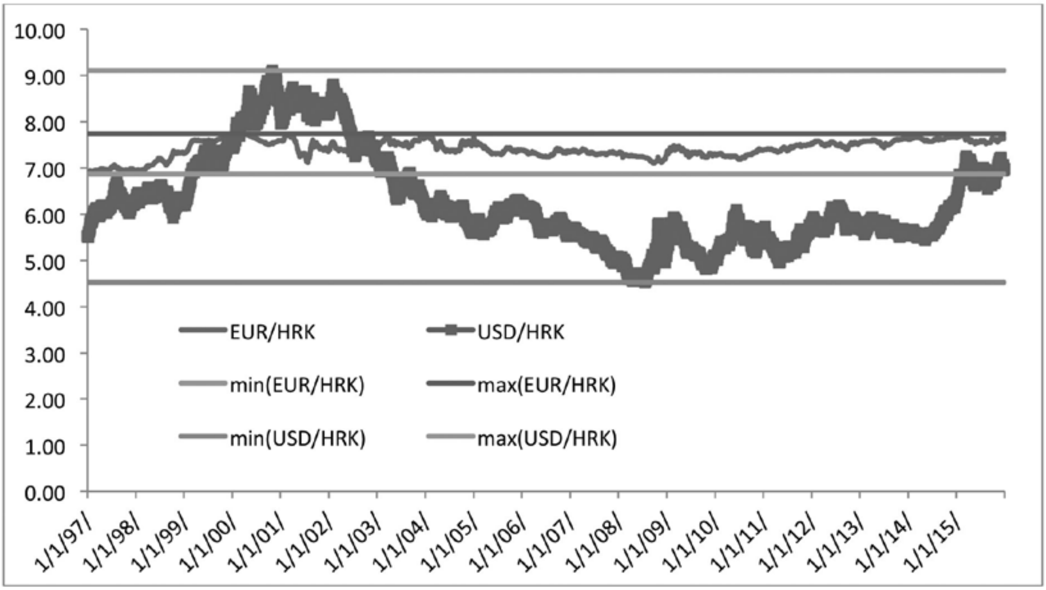
Generalized Autoregressive Conditional Heteroskedastic (GARCH) models have become important in the analysis and forecast of volatility in financial time series. The number of GARCH models is extremely large, but the most influential models were the first. Engle (1982) introduced the ARCH model. The main purpose of the autoregressive conditional heteroscedasticity (ARCH) model is to estimate the conditional variance of a time series. Engle described the conditional variance by a simple quadratic function of its lagged values. The phenomenon of leptokurtosis in exchange rates changes that have been documented by a number of studies and ARCH effects are consistent with the phenomenon of leptokurtosis (McFarland, 1982). Bollerslev (1986) extended the basic ARCH model and described the conditional variance by its own lagged values and the square of the lagged values of the innovations or shocks. Nelson (1991) formulated the Exponential GARCH (EGARCH) model by extending the GARCH model to capture news in the form of leverage effects. Afterwards, the GARCH model extension was developed to test for this asymmetric news impact (Glosten et al., 1993; Zakoian, 1994). Ding et al. (1993) extensions nest a number of models from the ARCH family. Hsieh (1989) proved on the daily data sample during a 10-year period (1974 – 1983) for five countries in comparison to the US dollar, that these two models, the ARCH and GARCH models were capable to remove all heteroscedasticity in price changes. It was also proved that the standardized residuals from each of the ARCH and GARCH models using the standard normal density were highly leptokurtic, and the standard GARCH (1, 1) and EGACH (1, 1) were found to be efficient for removing conditional heteroscedasticity from daily exchange rate movements. Olowe (2009) modeled volatility of Naira/US Dollar exchange rates on a sample of monthly data from 1970 to 2007. Six different GARCH models were tested. The paper concluded that the best fitted models are the Asymmetric Power ARCH and the Threshold Symmetric GARCH. Marreh et al. (2014) modeled the Euro/GMD and USD/GMD daily returns on a sample period from 2003 to 2013. Based on Akaike information criteria authors found the ARMA (1, 1) – GARCH (1, 1) and the ARMA (2, 1) – GARCH (1, 1) the best fitting models. The GARCH (1, 1) is found to be the most frequently used model in describing volatility in the literature as well as in market analyses (Berüment and Günay, 2003; Oduncu, 2011). Ngowani (2012) using daily exchange rate data from 2009 to 2011 found GARCH (1, 1) the best fitted model explaining the USD/RMB exchange rate volatility. Ullah et al. (2012) found GARCH (1, 1) as the best fitted model describing the Rupee behavior pattern. On a data sample from 1978 to 2009, Arabi (2012) modeled the Sudanese pound daily exchange rate volatility and found EGARCH (1, 1) to be the best fitted model indicating the existence of the leverage effect. Çağlayan et al. (2013) found EGARCH as the best forecasting model for Mexico. As discussed earlier, many researchers have used the ARCH and GARCH models to study high-frequency time series of foreign exchange rates as they usually provide a better fit compared to other constant variance models. In line with previous researches, selection of an appropriate model is the key instrument to determine the EUR/HRK as well as the USD/HRK exchange rate pattern behavior.

3. Exchange rate in Croatia and its fluctuation constraints

Even though the exchange rate is an important topic especially for small open economies like Croatia and there has been an extensive debate about the exchange rate adequacy, the literature on the EUR/HRK as well as on the USD/HRK exchange rate is relatively scarce. Due to the high degree of openness in the Croatian economy and the relatively high external debt position, at first level rank, the exchange rate pattern behavior becomes more and more important. Furthermore, the exchange rate volatility topic is of extreme importance in Croatia since the majority of the bank placements are indexed to foreign currency, mainly to the EUR. In order to meet its primary objective and maintain stable prices, the Croatian National Bank keeps the EUR/HRK exchange rate stability (Palić et al., 2014; Mance et al., 2015). Figure 1 shows the EUR/HRK and the USD/HRK Croatian National Bank midpoint exchange rate movements from January 1997 to September 2015.

As can be seen in Figure 1, the EUR/HRK exchange rate movements range is much tighter in comparison to the USD/HRK movements range.

Figure 1 The EUR/HRK and the USD/HRK exchange rate movements from January 1997 to September 2015



Source: Authors

In accordance to Lang (2005), exchange rate volatility is the main driving force of Croatian foreign exchange intervention while the exchange rate level turns out to be insignificant. According to Chmelarova and Schnabl (2006), Croatian foreign exchange intervention manages both day-to-day exchange rate volatilities as well as exchange rate levels. Furthermore, the authors concluded that the pattern of foreign exchange intervention for Croatia confirms a fear of depreciation (with respect to balance sheet effects of the banking sector) more than a fear of appreciation (with respect to export competitiveness). Following the previous research results and empirical data on exchange rate movements, the EUR/HRK exchange rate might be strictly controlled by the Croatian National Bank. Since the Croatian National Bank cannot control the USD/HRK exchange rate at the same time, it's interesting to compare the EUR/HRK and the USD/HRK volatilities pattern.

4. Research data

Financial time series often exhibit volatility clustering, meaning that high volatility periods tend to be followed by high volatility periods and low volatility periods tend to be followed by low volatility periods. In that case, a strong autocorrelation in squared returns or autoregressive conditional heteroscedasticity is present. As a consequence, the least squares estimators are still unbiased but inefficient. The estimates of the variances are biased, thus invalidating the tests of significance, and the obtained results are dubious (see for example Erjavec and Cota, 2007). In order to resolve the problem and obtain estimator efficiency, as a method of estimation several ARCH type models has been employed. As in most empirical finance literature, the variable to be modeled is the daily exchange rate return which is the first difference of the natural logarithm of the exchange rate and is given by the following equation:

$$r_t = \ln\left(\frac{S_t}{S_{t-1}}\right) \tag{1}$$

Where r_t is the daily exchange rate return and S_t and S_{t-1} denote the Croatian National Bank (CNB) midpoint exchange rate of the EUR versus the HRK and the USD versus the HRK at the current day and previous day, respectively. The data span from 1st January 1997 to 30th September 2015 is used as a data sample for modeling the daily exchange rate return. Table 1 shows the descriptive statistics for the observed variables.

Table 1 Descriptive statistics for the daily exchange rates return of the EUR and the USD versus the HRK

Variable	$r_{t\text{-}EUR}$	$r_{t\text{-}USD}$
Mean	2.34E-05	4.36E-05
Median	1.44E-05	-7.19E-05
Maximum	0.010004	0.035861
Minimum	-0.008836	-0.035029
Std. Dev	0.001345	0.006620
Skewness	0.081265	0.018182
Kurtosis	6.346057	4.453776
Jarque-Bera	2199.145	414.4102
Probability	0.000000	0.000000
Number of observations	4703	4703

Source: Authors' calculation

A key feature of exchange rate returns is that the distribution of returns is fat tailed. That is, the probability density function of exchange rate returns appears to be leptokurtic, so it is more peaked at the center and has fatter tails compared to that of the normal distribution. Numerically, the kurtosis coefficient is found to be greater than 3, which characterizes kurtosis of a normally distributed random variable. In addition, exchange rate returns tend to be slightly skewed either to the left or to the right which is not consistent with returns being normally distributed. The positive value of skewness indicates that data are skewed to the right referring to a depreciation of the currency (HRK). As can be seen in Table 1, the exchange rate returns series (r_t) exhibits significant values of skewness and kurtosis, and therefore normality assumptions are not met. In accordance to abovementioned alternative, distributions have to be used as a basis for modeling exchange rate returns, such as the Student-t or Generalized Error distribution (GED) rather than the normal distribution which takes into account the phenomenon of leptokurtosis and skewness in the probability density function.

5. Methodology

Since time series are being modeled, stationarity properties of the observed time series needs to be checked first. In order to test stationarity properties of the observed time series an augmented Dickey–Fuller test (ADF) for a unit root in a time series sample is performed. Afterwards, using the ordinary least squares method (OLS) as an estimator, the foreign exchange rate moving pattern is estimated. The foreign exchange rate moving pattern might be an autoregressive (AR) process, moving average (MA) process or a combination of AR and MA processes i.e. (ARMA) process. For the purposes of this study the mean equation is modified to include appropriate AR and MA terms to control for autocorrelation in the data. For example, in ARMA (1, 1) process pattern would be:

$$Y_t = \sum_{i=1}^{p} \alpha_i \cdot Y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \beta_i \cdot \varepsilon_{t-i}, \tag{2}$$

where Y is a time series being modeled.

In accordance with autocorrelation and partial correlation within correlogram for each time series, a process pattern is assumed and the process pattern assumption for each time series is verified through diagnostic checking. Based on heteroscedasticity test results on residuals for each of the estimated foreign exchange rate moving patterns, further steps are performed. Heteroscedasticity of residuals in the estimated foreign exchange rate moving pattern is tested through the ARCH test i.e. Lagrange multiplier test to assess the significance of ARCH effects. If the ARCH effect is significant, several ARCH based models will be tested and compared. Based on the results, the tested models are specified. The GARCH (1, 1) conditional variance equation is given by equation (3):

$$\sigma_t^2 = \omega + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot \sigma_{t-1}^2, \tag{3}$$

where ω is a constant term, the ARCH term ε^2_{t-1} is given as the first leg of the squared residual from the mean equation and represents news about the volatility from the previous period, and the GARCH term σ^2_{t-1} represents last period's forecast variance. The ARCH (1) conditional variance equation contains no GARCH term. The ARCH (1) is given by equation (4):

$$\sigma_t^2 = \omega + \alpha \cdot \varepsilon_{t-1}^2 \tag{4}$$

The specification of this model is consistent with the volatility clustering often seen in financial returns data, where large changes in returns are likely to be followed by large changes and small changes are likely to be followed by small changes. It is often observed in financial markets research that a downward price movement in the market will generate a higher volatility response than an equivalent upward movement. This is described as the asymmetric news impact. The TARCH specification by Glosten, Jaganathan and Runkle (1993), as well as Zakoian (1994), is used to test for this asymmetric news impact. The occurrence of an extremely short period of spikes followed by periods of relative calm is a well-known property of financial time series. The TARCH specification for the conditional variance is:

$$\sigma_t^2 = \omega + \alpha \cdot \varepsilon_{t-1}^2 + \gamma \cdot \varepsilon_{t-1}^2 \cdot d_{t-1} + \beta \cdot \sigma_{t-1}^2 \tag{5}$$

The model is based on the assumption that unexpected changes in the exchange rate returns expressed in terms of ε_t , have different effects on the conditional variance of exchange rate returns. So, the basic GARCH model of equation (3) is extended to include a threshold term $\gamma \cdot \varepsilon^2_{t-1} \cdot d_{t-1}$. In this model, $d_t=1$ if $\varepsilon_t<0$ and 0 otherwise. In this model, an upward spike means $\varepsilon_t<0$ has an impact of α and downward or negative news $\varepsilon_t<0$ has an impact of α+γ. If γ >0, a negative news increases volatility and a leverage effect is present. If γ≠0, the impact of news on the series returns is asymmetric. The asymmetric volatility response noted by Higgs and Worthington (2005) indicates that volatility tends to rise in response to positive spikes and fall in response to negative spikes, which is an asymmetry that runs counter to the effects generally observed in financial markets. The Exponential GARCH (EGARCH) introduced by Nelson (1991) specifies the conditional variance in logarithmic form:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \cdot \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \cdot \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \cdot \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \tag{6}$$

The left-hand side is the log of the conditional variance, implying that any leverage effects are exponential and that forecasts of conditional variance are guaranteed to be non-negative. The form of the equation indicates that conditional variance is an exponential function of the variables under analysis, which ensures its positive character. In interpreting the model, the impact is asymmetric if $\gamma k \neq 0$ and the presence of leverage effects is indicated by $\gamma k<0$. The exponential form of EGARCH ensures that external unexpected shocks will have a stronger influence on the predicted volatility than in TARCH. The Power-ARCH (PARCH) specification introduced by Ding et al. (1993) generalizes the transformation of the error term in the models. The PARCH specification is given by equation (7):

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{q} \beta_j \cdot \sigma_{t-j}^{\delta} + \sum_{i=1}^{p} \alpha \cdot (|\varepsilon_{t-1}| - \gamma_i \cdot \varepsilon_{t-i})^{\delta} \tag{7}$$

The power parameter, δ, in this model is not imposed but estimated, and a threshold parameter, γ, is included to capture for asymmetry. The Bollerslev (1986) model sets $\delta=2$, $\gamma=0$, and the Taylor (1986) model sets $\delta=1$and $\gamma=0$. Empirical literature shows that the power term is sample dependent and in case of stock data often amounts to near unity (Ding et al., 1993), while in case of foreign exchange data often amounts between unity and two (Mitchell and McKenzie, 2008). In terms of criteria for selecting the best model, the Akaike information criterion (AIC) and Schwarz Criterion (SC) are estimated and compared for all the specified volatility models.

6. Empirical results and discussion

In accordance with the Augmented Dickey–Fuller test results shown in Table 2, one can conclude that the daily exchange rate return of the EUR versus the HRK as well as the USD versus the HRK is a stationary time series around zero.

The existence of the degree of autocorrelation and the partial autocorrelation between the data considered and the results of the Ljung-Box Q test performed on the squared residuals were verified. Because of the p-value (all zero), the hypothesis of zero correlation between the data series was rejected, which is also demonstrated by the

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

Variable		p - value
$r_{t\text{-}EUR}$	around zero	0.00
$r_{t\text{-}USD}$	around zero	0.00

Source: Authors' calculation

autocorrelation values that are different from zero. In regards to autocorrelation and partial autocorrelation, the following assumptions are made:

- the daily USD/HRK exchange rate return time series ($r_{t\text{-}USD}$) can be modeled as an AR (1) process since the values of the autocorrelations decrease but never nullify and at the same time the partial autocorrelation is relevant for the first and second term.
- the daily EUR/HRK exchange rate return time series ($r_{t\text{-}EUR}$) can be modeled as an AR (3) process since the values of the autocorrelations decrease but never nullify and at the same time the partial autocorrelation is relevant for first, second and third term.

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

Table 3 shows estimation results for the USD/HRK daily exchange rate return model (mean equation).

Table 3 Estimation results for AR (1) daily exchange rate return of the USD versus the HRK (mean equation)

Variable	Coefficient	Prob.
AR(1)	-0.030004	0.0396

Source: Authors' calculation

Afterwards, the diagnostic checking results using the Breusch-Godfrey Serial Correlation LM Test and correlogram show no serial correlation among residuals in the estimated model in Table 3 and significant ARCH effects (p-value amounts 0.00).

Table 4 shows estimation results for the EUR/HRK daily exchange rate return model (mean equation).

Table 4 Estimation results for AR (3) daily exchange rate return of the EUR versus the HRK (mean equation)

Variable	Coefficient	Prob.
AR(2)	0.242479	0.0000
AR(3)	0.092783	0.0000

Source: Authors' calculation

The diagnostic checking results using the Breusch-Godfrey Serial Correlation LM Test and correlogram show no serial correlation among residuals in the estimated mean equation model in Table 4 but the ARCH effect in residuals of mean equation is significant (p-value amounts 0.00). Since the ARCH effect is significant, ARCH family models can be estimated. Table 5 shows mean and variance equations estimates for the EUR/HRK exchange rate return using Student t distribution. Table 6 shows mean and variance equation estimates for the EUR/HRK exchange rate return using Generalized Error Distribution. Table 7 shows mean and variance equations estimates for the USD/HRK exchange rate return using Student t distribution. Table 8 shows mean and variance equation estimates for the USD/HRK exchange rate return using Generalized Error Distribution.

Table 5 Mean and variance equation estimates for the EUR/HRK exchange rate return using Student t distribution

Parameter	ARCH (1)	ARCH (2)	GARCH (2,1)	TARCH	EGARCH	PARCH
AR(2)	0.220930	0.217083	0.212264	0.212264	0.212514	0.212069
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
AR(3)	0.089504	0.087926	0.081667	0.081667	0.076607	0.081235
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ω	1.10E-06	8.29E-07	8.72E-09	8.72E-09	-0.285027	2.02E-08
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.6115)
α_1	0.449534	0.387770	0.192362	0.192352	0.356793	0.194216
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_2		0.225062	-0.122516	-0.122520	-0.189053	-0.122347
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β			0.928510	0.928514	0.988406	0.928929
			(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ				2.35E-05	0.003608	6.49E-05
				(0.9980)	(0.6739)	(0.9966)
δ						1.881836
						(0.0000)
ARCH - LM Test	(0.0129)	(0.0900)	(0.2609)	(0.2609)	(0.5094)	(0.2919)
AIC	-1062623	-1065309	-1073867	-1073825	-1073593	-1073787
SC	-1061936	-1064485	-1072906	-1072726	-1072494	-1072551
Obs	4703	4703	4703	4703	4703	4703

Source: Authors' calculation

Table 6 Mean and variance equation estimates for the EUR/HRK exchange rate return using Generalized Error Distribution

Parameter	ARCH (1)	ARCH (2)	GARCH (2,1)	TARCH	EGARCH	PARCH
AR(2)	0.220598	0.217391	0.213090	0.213172	0.212660	0.212785
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
AR(3)	0.082649	0.081453	0.080095	0.080171	0.075244	0.079614
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ω	1.09E-06	8.37E-07	9.09E-09	9.20E-09	-0.288493	2.82E-08
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.6145)
α_1	0.397674	0.357555	0.177265	0.179166	0.334796	0.179743
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_2		0.207085	-0.107581	-0.107072	-0.167381	-0.106931
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β			0.927698	0.927297	0.988171	0.927752
			(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ				-0.004267	0.006639	-0.006570
				(0.6867)	(0.4136)	(0.6836)
δ						1.842740
						(0.0000)
ARCH - LM Test	(0.0363)	(0.1466)	(0.4818)	(0.4823)	(0.8443)	(0.5444)
AIC	-1062333	-1064944	-1073754	-1073714	-1073494	-1073680
SC	-1061646	-1064120	-1072792	-1072616	-1072396	-1072444
Obs	4703	4703	4703	4703	4703	4703

Source: Authors' calculation

Table 7 Mean and variance equation estimates for the USD/HRK exchange rate return using Student t distribution

Parameter	ARCH (1)	GARCH (1,1)	TARCH	EGARCH	PARCH
AR(1)	-0.036793	-0.034858	-0.034922	-0.034727	-0.034965
	(0.0194)	(0.0194)	(0.0191)	(0.0196)	(0.0190)
ω	3.76E-05	1.02E-07	9.98E-08	-0.128393	1.86E-05
	(0.0000)	(0.0454)	(0.0489)	(0.0000)	(0.5612)
α	0.142786	0.033840	0.034975	0.081405	0.041303
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β		0.964669	0.965069	0.993583	0.962464
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ			-0.003015	0.005264	-0.060045
			(0.6342)	(0.3220)	(0.3815)
δ					1.114755
					(0.0000)
ARCH - LM Test	(0.3792)	(0.4355)	(0.4406)	(0.4486)	(0.4443)
AIC	-7244970	-7323081	-7322705	-7324813	-7324002
SC	-7239478	-7316216	-7314467	-7316575	-7314391
Obs	4703	4703	4703	4703	4703

Source: Authors' calculation

Table 8 Mean and variance equation estimates for the USD/HRK exchange rate return using Generalized Error Distribution

Parameter	ARCH (1)	GARCH (1,1)	TARCH	EGARCH	PARCH
AR(1)	-0.036998	-0.036325	-0.036390	-0.036269	-0.036343
	(0.0171)	(0.0.0141)	(0.0138)	(0.0140)	(0.0137)
ω	3.74E-05	1.38E-07	1.31E-07	-0.131744	4.93E-05
	(0.0000)	(0.0040)	(0.0058)	(0.0000)	(0.5203)
α	0.140948	0.032765	0.035034	0.078274	0.039778
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β		0.964683	0.965499	0.993014	0.962640
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ			-0.005939	0.008200	-0.111056
			(0.3021)	(0.0843)	(0.1050)
δ					0.965157
					0.0004)
ARCH - LM Test	(0.4058)	(0.5115)	(0.5280)	(0.5264)	(0.5457)
AIC	-7244451	-7319053	-7318830	-7321435	-7320713
SC	-7238959	-7312188	-7310592	-7313197	-7311103
Obs	4703	4703	4703	4703	4703

Source: Authors' calculation

Comparing the estimated results in Tables 5 and 7 with the estimated results in Tables 6 and 8 no significant difference can be found between using Students t distribution and Generalized error distribution. According to the Q-statistic, there is no serial correlation among residuals in any of the estimated ARCH family models. Out of compared Akaike information criterion (AIC) and Schwarz Criterion (SC) for all of the specified volatility models one can say that GARCH (2,1) is the best fitted model representing the daily EUR/HRK exchange rate return volatility since it has the lowest AIC and SC values. In accordance to the GARCH (2, 1) estimated parameters in Table 5 (and similarly in Table 6) one can see that the ARCH and GARCH coefficients and are statistically significant. The sum of these coefficients is 0.99 which indicates that shocks to volatility have a persistent effect on the conditional variance. The same results can be found in Table 7 and Table 8 for the USD/HRK exchange rate returns. These shocks will have a permanent effect if the sum of the ARCH and GARCH coefficients equals unity. In that case the conditional variance does not converge on a constant unconditional variance in the long run. The GARCH model assumes a symmetric response of volatility to past shocks. In accordance with Suliman and Suliman (2012), negative shocks imply a higher next period volatility of daily exchange rate return than positive shocks. In order to test whether good news and bad news have differential effects on the conditional variance, the TARCH, EGARCH and PARCH models have been estimated. If bad news increases volatility one can say that there is a leverage effect. As can be seen in Table 5, Table 6, Table 7 and Table 8, there is no empirical evidence that negative and positive shocks imply a different next period volatility of the daily exchange rate return. Furthermore, the model representing the mean equation for the EUR/HRK exchange rate returns takes the AR(3) form while the equation for the EUR/HRK exchange rate returns takes the AR(1) form. The model representing the variance equation for the USD/HRK exchange rate returns takes the GARCH (2, 1) form while the equation for the USD/HRK exchange rate returns takes the GARCH (1, 1) form. Engle (2001) points out that the GARCH (1, 1) model is the simplest and the most robust of volatility models and has proved sufficient for most financial market data. According to Bhargava and Davinder (2007), numerous previous studies have shown that the conditional variance of the GARCH (1, 1) model is the appropriate volatility measure for currencies. The research results out of the estimated USD/HRK volatility pattern are consistent with previous research and shows that the GARCH (1, 1) outperforms other volatility models. In regards to the EUR/HRK volatility pattern, we found slightly different results. The GARCH (1, 1) is not the appropriate model form to describe the EUR/HRK exchange rate volatility, since this form still shows heteroscedasticity in variance. In order to capture the EUR/HRK exchange rate volatility pattern, the model needs to be extended up to the GARCH (2, 1) form. This might be the case due to the high euroization in the Croatian banking sector and the Croatian National Bank's control over the EUR/HRK exchange rate.

7. Conclusion

Many researchers have used the ARCH and GARCH models to study the high-frequency time series of foreign exchange rates as they usually provide a better fit compared to other constant variance models. This paper investigates the EUR/HRK and the USD/HRK exchange rate volatility using variants of GARCH volatility models and compares estimates from these models. The probability density function of exchange rate returns appears to be leptokurtic, so it is more peaked at the center and has fatter tails compared to that of the normal distribution. No difference in the estimated models was found using Student t distribution in comparison to using Generalized Error distribution. The mean equation in the EUR/HRK exchange rate returns can be explained as an AR (3) process. Out of the compared Akaike information criterion (AIC) and Schwarz Criterion (SC) for all of the specified volatility models one can say that the GARCH (2,1) model is the best fitted model. The mean equation in USD/HRK exchange rate returns can be explained as an AR (1) process. Out of the compared Akaike information criterion (AIC) and Schwarz Criterion (SC) for all of the specified volatility models one can say that the GARCH (1,1) model is the best fitted model. In accordance with the estimated models there is no empirical evidence that negative and positive shocks imply different next period volatility of the daily EUR/HRK or USD/HRK exchange rate return. Therefore, no leverage effect has been found daily in the EUR/HRK or in the USD/HRK exchange rate return. Eventually, even though the EUR/HRK exchange rate is said to be under strict control of the Croatian National Bank it can be modeled using GARCH models. Further researches may be directed toward the relationship between the here determined EUR/HRK or USD/HRK pattern behavior and other relevant macroeconomic variables in Croatia.

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Modeliranje volatilnosti deviznog tečaja u Hrvatskoj

Sažetak

Modeliranje i predviđanje volatilnosti deviznog tečaja ima važne implikacije u području makroekonomije i financija. Empirijska istraživanja volatilnosti deviznog tečaja u različitim zemljama i regijama, rezultirala su razvojem brojnih modela. Dobro poznati i često primjenjivani modeli za procjenu volatilnosti deviznog tečaja su autoregresijski modeli uvjetne heteroskedastičnosti (ARCH) kojega je razvio Engle (1982) i generalizirani model uvjetne heteroskedastičnosti (GARCH) kojega su neovisno razvili Bollerslev (1986) i Taylor (1986). U radu se na uzorku dnevnih podataka deviznog tečaja EUR/HRK i USD/HRK u razdoblju od 1997. do 2015. procjenjuje i uspoređuje nekoliko ARCH modela. Prema standardnim informacijskim kriterijima GARCH (2,1) model najbolje opisuje dnevnu volatilnost deviznog tečaja EUR/HRK dok GARCH (1,1) model najbolje opisuje dnevnu volatilnost deviznog tečaj USD/HRK. U skladu s procijenjenim modelima, nema empirijskih dokaza da pozitivni i negativni skokovi različito utječu na volatilnost deviznih tečajeva EUR/HRK i USD/HRK u narednom razdoblju.

Ključne riječi: GARCH model, heteroskedastičnost, volatilnost deviznog tečaja, Hrvatska