DETECTING REGIME SWITCHES IN THE EUR/RON EXCHANGE RATE VOLATILITY

Necula Ciprian
The Academy of Economic Studies The Faculty of Finance and Banking Bucharest ciprian.necula@fin.ase.ro
Radu Alina-Nicoleta
The Academy of Economic Studies The Faculty of Finance and Banking Bucharest alinanicoleta.radu@gmail.com

In the present study we develop and implement a short term exchange rate forecasting methodology using dynamic confidence intervals based on GARCH processes and we analyze whether this methodology can be used to model a regime switch in the volatility of the EUR/RON exchange rate generated by the change of the reference currency from USD to EUR in March 2003. In order to capture this switch we use in our analysis daily exchange rate returns from 1st of January 1999 to 1st of January 2004. We model the dynamics of the daily returns for the exchange rate by estimating a series of GARCH models, with various specifications for the conditional mean and for the conditional variance. The best specification is a FIGARCH (1, d, 0), a long memory process accounting for volatility persistence. The main finding is that there was a significant decrease in the volatility of the EUR/RON exchange rate after March 2003.

Keywords: conditional heteroskedasticity, regime switch, exchange rates, long memory

JEL Classification: C01, C15, C51, C87, E44, E47

1. Introduction

Daily frequency financial data series present some specific characteristics, such as the „volatility clustering" phenomenon. This phenomenon refers to the fact that on the capital market the conditional variance of the return series is not constant, but variable in time. Nowadays, modeling the volatility of assets returns is the research frontier in financial theory. In order to have a proper analysis of the „volatility clustering" phenomenon, Engle (1982) introduced ARCH (AutoRegressive Conditional Heteroskedasticity) processes and Bollerslev (1986) developed a more parsimonious model, GARCH (Generalized ARCH).

To account for the high levels of kurtosis in the distribution of daily returns, a series of GARCH models with "fat-tails" innovations were developed. The Student distribution was employed by Bollerslev (1987) and Kaiser (1996), Nelson (1991) analyzed the „Generalized Error Distribution" (GED) and Lambert and Laurent (2001) developed a GARCH model with an asymmetric Student distribution. Numerous studies (Harvey, 1993; Ding, Granger and Engle, 1993; Briedt, Crato and Lima, 1998) conclude that the volatility of financial assets is persistent. To model this persistence various GARCH processes with long memory were proposed in the literature. In this category one can mention FIGARCH models (Fractionally Integrated GARCH) developed by Baillie, Bollerslev and Mikkelsen (1996), Bollerslev and Mikkelsen (1996) and Chung (1999).

In the present study we develop and implement a short term exchange rate forecasting methodology using dynamic confidence intervals. The confidence intervals length is variable, since it depends on the volatility forecast obtained from a GARCH process. We analyze whether this methodology based on GARCH stochastic processes can be used to model a regime switch in the volatility of the EUR/RON exchange rate generated by the change of the reference currency from USD to EUR in March 2003. We model the dynamics of the daily return for the exchange rate by estimating a series of GARCH models, with various specifications for the conditional mean and for the conditional variance.

The paper is organized in three sections. In the first section we develop a dynamic confidence interval forecasting methodology based on GARCH processes. In the second section we estimate a series of GARCH model specifications using daily EUR/RON the exchange rate returns. The final section concludes.

2. Exchange Rates Forecasting using Dynamic Confidence Intervals

In order to model the dynamics of daily exchange rate returns, we employ a series of GARCH models with various specifications for the conditional mean and for the conditional variance. Therefore, the daily return series is modeled as

$$r_t = E_{t-1}(r_t) + \varepsilon_t \qquad (1)$$

where $E_t(\cdot)$ is the conditional mean, and ε_t represents the innovations, with the following properties $E(\varepsilon_t) = 0, E(\varepsilon_t \varepsilon_s) = 0, \forall t \neq s$. GARCH models imply that conditional variance is not constant in time. Therefore, one can write

$$\varepsilon_t = z_t \sigma_t \qquad (2)$$

where z_t i.i.d with $E(z_t) = 0, Var(z_t) = 1$, and σ_t^2 is the conditional variance that will be modeled using different specifications.

In order to discriminate between various model specifications we employ several informational criteria. We also perform a series of stability tests for the parameters of these models.

Regarding exchange rate forecasting, we employ a dynamic confidence interval methodology based on the conditional variance forecast obtained from the GARCH models. Hence, the 95% confidence interval for the one day return is

$$\left(\hat{r}_{t+1|t} + z_{0.025}\hat{\sigma}_{t+1|t}, \hat{r}_{t+1|t} + z_{0.975}\hat{\sigma}_{t+1|t}\right) \qquad (3)$$

where $\hat{r}_{t+1|t}$ is the forecast for the expected one day return, $\hat{\sigma}_{t+1|t}$ the one day forecast of the volatility, and $z_{0.025}$ and $z_{0.975}$ are the 2.5% and 97.5% quantiles of the theoretical distribution employed in the GARCH model. In conclusion, the 95% confidence interval for $\ln P_{t+1}$ (i.e. the logarithm of the spot exchange rate at $t+1$) is

$$\left(\ln P_t + \hat{r}_{t+1|t} + z_{0.025}\hat{\sigma}_{t+1|t}, \ln P_t + \hat{r}_{t+1|t} + z_{0.975}\hat{\sigma}_{t+1|t}\right). \qquad (4)$$

In case one wants to obtain confidence intervals for a period of h days, one can use the h-days expected return forecast

$$\hat{R}_{t+h|t} = \sum_{i=1}^{h} \hat{r}_{t+i|t} \qquad (5)$$

and the h-days volatility forecast

$$\hat{V}_{t+h|t}^2 = \sum_{i=1}^{h} \hat{\sigma}_{t+i|t}^2 \qquad (6)$$

In these conditions, the 95% confidence interval for the h-days return is

$$\left(\hat{R}_{t+1|t} + z_{0.025}\hat{V}_{t+1|t}, \hat{R}_{t+1|t} + z_{0.975}\hat{V}_{t+1|t}\right) \qquad (7)$$

and the 95% confidence interval for $\ln P_{t+h}$ is

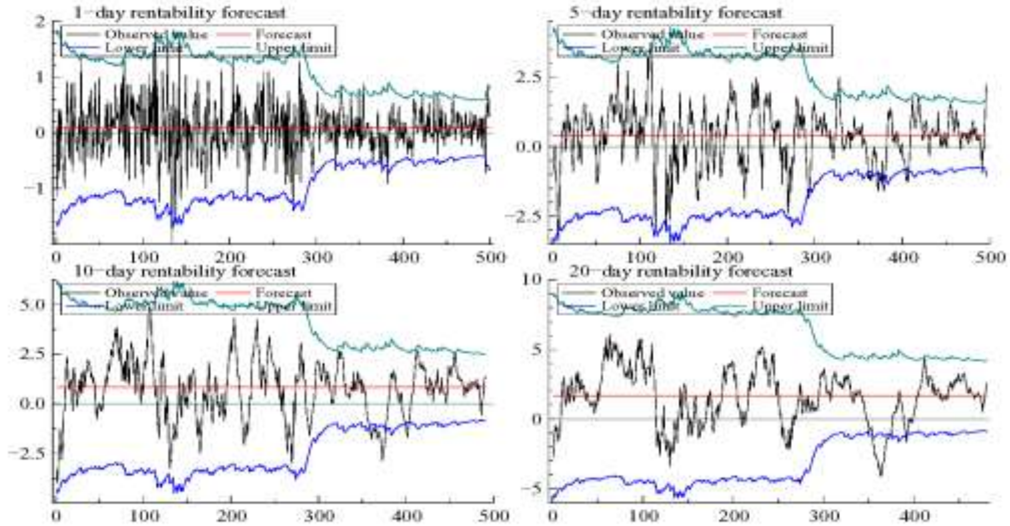
$$\left(\ln P_t + \hat{R}_{t+h|t} + z_{0.025}\hat{V}_{t+h|t}, \ln P_t + \hat{R}_{t+h|t} + z_{0.975}\hat{V}_{t+h|t}\right) \qquad (8)$$

3. Forecasting the EUR/RON exchange rate volatility

In this section we analyze whether the methodology based on GARCH processes can accurately model a regime switch in the volatility of the EUR/RON exchange rate generated by the change of the reference currency from USD to EUR in March 2003. In order to capture this switch we use in our analysis daily exchange rate returns from 1st of January 1999 to 1st of January 2004. First we tested for normality and for heteroskedasticity in the daily EUR/RON exchange rate returns. The Jarque-Bera test rejects the null hypothesis of normal returns. The existence of the autocorrelation in the squared returns (according to Box Pierce Q test) and the existence of the ARCH effects (according to the Engle's ARCH LM test) entail the usage of a GARCH model to account for volatility clustering.

The first estimated model is a classical GARCH (1, 1) model with normal innovations and a constant in the equation of the conditional mean. The estimated parameters are statistically significant, the GARCH process is stationary, but with volatility persistence. The BoxPierce Q test and the ARCH LM test for the squared standardized residues imply that the conditional variance equation is correctly specified. The BoxPierce Q test for the standardized residues suggests that the mean equation is also correctly specified. Since only a constant is required to explain the conditional mean, the EUR/RON exchange rate return dynamics is quite difficult to forecast. The Nyblom stability test rejects the null hypothesis that parameters of the estimated model are stable (i.e. constant in time). As a consequence, we introduced a dummy variable to account for the moment the Central Bank changed the reference currency in March 2003. Henceforth, we estimated a GARCH (1, 1) model with normal innovations and a dummy variable in the conditional variance equation. The parameters of this model are stable, implying that there are no more volatility switches in the analyzed period. Also, according to the informational criteria, this model is superior to the previous one. Figure 1 depicts 1, 5, 10 and 20 days forecasts for the EUR/RON exchange rate return generated by the dummy – GARCH (1, 1) model with normal innovations.

Figure 1 - 95% confidence intervals for the EUR/RON exchange rate return for the estimated dummy - GARCH (1, 1) model with normal innovations and a constant in the mean equation



As one can notice, the EUR/RON exchange rate volatility decreased from the moment the

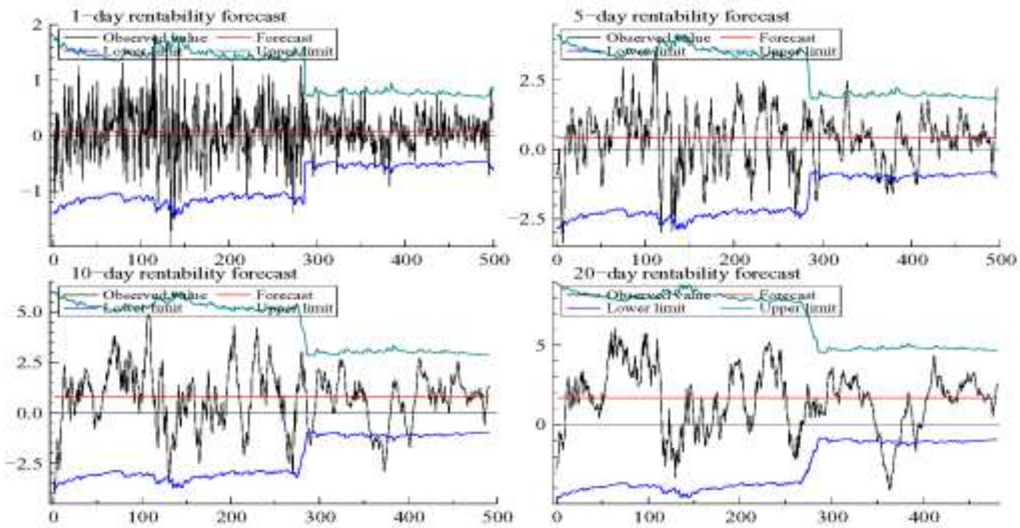
Central Bank introduced euro as the reference currency. This shift in volatility was probably generated by Central Bank interventions on the FOREX market.
The tests conducted on the residues of the two estimated GARCH models imply that the innovations are not normally distributed. This distribution is leptokurtic and asymmetrical. As a result we estimated a series of dummy - GARCH (1, 1) models having innovations with GED distribution, Student distribution or asymmetric Student distribution. Table 1 presents quality indicators for these models: Akaike informational criterion (AIC), Schwartz informational criterion (BIC), Pearson distribution comparison test, and Nyblom stability test.

Table 1 Quality indicators for the estimated dummy - GARCH (1, 1) models with various distributions for the innovations

Indicator	**Innovations` distribution**			
	Normal	**GED**	**Student**	**Asymmetric Student**
AIC statistic	1.932326	1.908004	1.894860	1.889276
BIC statistic	1.952563	1.932288	1.919145	1.917608
Pearson p-value	0.021586	0.059488	0.056443	0.176441
Nyblom statistic	0.970891	1.42561	1.32591	1.43361

The Pearson test for the estimated GARCH (1, 1) model with an asymmetric distribution of the innovations indicated a higher probability than for the other estimated models that the theoretical distribution is identical to the empirical one. In addition, according to the informational criteria, the asymmetric Student distribution model is superior to the other GARCH (1, 1) processes. This can be explained by the fact that the theoretical distribution is not only leptokurtic, but also asymmetrical, implying a better fit to the empirical distribution.
Next, we used some other specifications for the conditional variance equation. For the beginning, we tested for the existence of a leverage effect in the EUR/RON exchange rate return series. The test was conducted using two asymmetrical GARCH models. The estimations of the TARCH and APARCH models concluded that the parameter that account for the leverage effect is not statistically significant. It is important to mention that all the estimated models present a high persistence of the volatility. In order to model this persistence we estimated a series of integrated GARCH models. First an IGARCH (1, 1) model was used. The parameters are statistically significant and stable in time. But, according to the informational criteria, this model is not superior to the estimated GARCH (1, 1) models. As a consequence, we modeled the persistence in volatility using a long memory process. Therefore, we estimated a FIGARCH (1, d, 0) model with asymmetric Student distribution. The Box Pierce and ARCH LM tests imply that the mean and variance equations are correctly specified and the Nyblom test suggests that the parameters are stable. Also, the Pearson test can not reject the null hypothesis that the empirical and theoretical distributions of the innovations are identical. In addition, according to the informational criteria, this model is the best from the ones estimated for the EUR/RON exchange rate. Figure 2 depicts 1, 5, 10 and 20 days forecasts for the EUR/RON exchange rate return generated by the dummy – FIGARCH(1, d, 0) model with asymmetric Student innovations. Also, as in the case of the other models, one can notice a significant decrease in the EUR/RON exchange rate volatility after the moment the Central Bank introduced euro as the reference currency.

Figure 2 - 95% confidence intervals for EUR/RON exchange rate return for the estimated dummy - FIGARCH (1, d, 0) model with asymmetric Student innovations and a constant in the mean equation



Having identified the best specification for the variance equation, next, we modeled the conditional mean using autoregressive processes. The only statistically significant specification consists of an ARFIMA (1, d, 0), a long memory process. The Nyblom test implies that the parameters are stable, and the Box Pierce Q and ARCH LM tests suggest that the mean equation and the conditional variance are correctly specified. However, according to the informational criteria, this model is not superior to the models that have only a constant in the equation of the conditional mean.

4. Concluding remarks

In the present study we analyzed whether a dynamic confidence intervals forecasting methodology based on GARCH processes can be used to model a regime switch in the volatility of the EUR/RON exchange rate generated by the change of the reference currency from USD to EUR in March 2003. In order to capture this switch we used in our analysis daily exchange rate returns from 1st of January 1999 to 1st of January 2004.

We estimated a series of GARCH models, with various specifications for the conditional mean and for the conditional variance. The best specification for the mean equation is a constant specification. Due to the simplicity of the mean equation the EUR/RON exchange rate return dynamics is quite difficult to forecast. The best specification for the variance equation consists of a FIGARCH (1, d, 0), a long memory processes that accounts for the persistence in volatility. The results of the parameter stability tests entailed the introduction of a dummy variable to account for the moment the Central Bank changed the reference currency.

The main finding of the study is that there was a significant decrease in the volatility of the EUR/RON exchange rate after March 2003. This shift in volatility was probably generated by Central Bank interventions on the FOREX market.

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