Journal of Forecasting
J. Forecast. **31**, 490–503 (2012)
Published online 20 February 2011 in Wiley Online Library
(wileyonlinelibrary.com) **DOI**: 10.1002/for.1214

Forecasting Stock Market Volatility in Central and Eastern European Countries

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ABSTRACT
In recent years, considerable attention has focused on modelling and forecasting stock market volatility. Stock market volatility matters because stock markets are an integral part of the financial architecture in market economies and play a key role in channelling funds from savers to investors. The focus of this paper is on forecasting stock market volatility in Central and East European (CEE) countries. The obvious question to pose, therefore, is how volatility can be forecast and whether one technique consistently outperforms other techniques. Over the years a variety of techniques have been developed, ranging from the relatively simple to the more complex conditional heteroscedastic models of the GARCH family. In this paper we test the predictive power of 12 models to forecast volatility in the CEE countries. Our results confirm that models which allow for asymmetric volatility consistently outperform all other models considered. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS CEE countries; stock market; volatility

INTRODUCTION

In recent years, considerable attention has focused on modelling and forecasting of stock market volatility. Stock market volatility matters because stock markets are an integral part of the financial architecture in market economies and play a key role in channelling funds from savers to investors. A certain amount of volatility is, of course, a natural recurring feature of stock market prices as funds are allocated among competing users. However, excessive volatility can impair the smooth functioning of the stock market and cause problems for firms seeking to raise risk capital and for the wider macroeconomy in general.

A major reason why the literature has focused on volatility is that it is an important measure of risk and plays a crucial role in portfolio management, option pricing and market regulation (see Poon and Granger, 2003, for a survey). For example, portfolio management stresses

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the necessity of balancing risk against expected return. Since a rise in volatility is taken to imply greater risk, this might discourage risk taking for a given expected return and lead investors to seek less risky assets. The overall effect of this, as noted by Guo (2002), is to increase the cost of capital to firms seeking to raise additional funds through an issue of stock. This could potentially impact on small firms and especially new firms as investors gravitate towards purchasing stock in larger and more well-established firms. More generally, if the cost of capital rises as investor preferences shift towards less risky assets in response to a perceived increase in volatility, this will also have implications for the macroeconomy since it is likely to discourage investment.

Changing equity prices cause changes in household wealth and there are good theoretical reasons why this might also impact on the macroeconomy through its effect on consumption spending. Testing this effect has yielded mixed results. Hall (1978) has argued that lagged stock prices are important in predicting future consumer spending. Other studies also find support for a link between changing equity prices and consumption (see, for example, Campbell, 2000; Kiley, 2000; Davis and Polumbo, 2001; Dynan and Maki, 2001). Stevans (2004) has shown that changes in wealth resulting from unanticipated changes in the value of equity holdings begin a process whereby households alter consumption growth in order to close the gap between actual and target spending. Bernanke and Gertler (1999) have argued that changes in asset prices impact on the real economy through the 'balance sheet channel'.

Most of the literature on volatility has focused on the developed stock markets of Europe, the USA and Japan. Only a few investigations have been carried out into volatility in the emerging stock markets of Central and Eastern Europe (CEE) (see, for example, Harvey *et al.*, 1997; Gilmore and McManus, 2001; Kash-Haroutounian and Price, 2001; Poshakwale and Murinde, 2001; Murinde and Poshakwale, 2002; Appiah-Kusi and Menyah, 2003; Salomons and Grootveld, 2003). In general, these studies conclude that stock market volatility in CEE markets tends to be relatively high compared with developed stock markets. One reason for this is that CEE markets are still comparatively young and, in terms of market capitalisation, volume traded and number of listed companies, are growing at a greater rate than developed markets.

The focus of this paper is on forecasting stock market volatility in CEE countries. Finance theory argues that returns ought to be higher where volatility is higher. Since, as noted above, volatility tends to be higher in CEE markets than in more fully developed markets, it follows that if volatility can be forecast it might be possible to make some general predictions about return behaviour. This is important because Harrison and Moore (2009) have argued that CEE markets display relatively weak co-movement with the developed markets of London and Frankfurt and therefore offer opportunities for portfolio diversification. The obvious question to pose, therefore, is how volatility can be forecast and whether one technique consistently outperforms other techniques. Over the years a variety of techniques have been developed ranging from the relatively simple to the more complex conditional heteroscedastic models of the GARCH family (see, for example, Andersen *et al.*, 2006a,b, for a review of the literature). In this paper, we test the predictive power of 12 models to forecast volatility in the CEE countries. Our results confirm that models that allow for asymmetric volatility consistently outperform all other models considered.

The rest of this paper is organised as follows. The next section provides a description of the data and the third section reviews the models used to test volatility. The fourth section reports our results and the fifth section provides a summary and conclusions.

DOI: 10.1002/for

DATA

This study uses daily observations on 10 stock exchanges in CEE countries (Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovenia and Slovak Republic) covering the period 1991–2008. The series were obtained from *Datastream International*. Stock market volatility is approximated by the squared residuals from an ARMA(1,1) model with a linear trend. The ARMA model is selected using the Akaike information criterion and the parameters of the autoregressive (AR) and moving average (MA) were statistically significant in all regressions.

Figure 1 provides a plot of volatility for each country and the descriptive statistics are provided in Table I. The figures reveal that stock market volatility is characterised by volatility clustering: a shock is likely to be followed by other (smaller) shocks. These volatility clusters correspond to the peaks and troughs of the returns series. Over the sample period considered, the stock exchanges in Bulgaria and Poland were the most volatile. Mean volatility on these two stock exchanges was 3.4 and 3.6, compared to 2.1 for the other stock markets in our study. Of the CEE countries investigated, Lithuania, the Slovak Republic and Slovenia were the least volatile. Corroborating evidence regarding the volatility of CEE exchanges can also be obtained by examining Figure 1.

As is usual with financial data, the distribution of returns appears to be non-normal, with estimated skewness for the volatility series well above zero. In addition, the measure of excess kurtosis for all the exchanges deviates significantly from that expected for observations drawn from a normal distribution. Non-normality is confirmed by the significance of the Jarque–Bera statistic (not reported here but available from the authors upon request).

VOLATILITY MODELS

One simple approach that can be employed to forecast volatility is to assume that n-step-ahead conditional variance is its past n-month average. This naïve model (NVOL) can be estimated by regressing the realised volatility on a constant. Thus the n-step-ahead forecast is given as

$$h_{t+n} = \overline{h} \tag{1}$$

This naïve approach to forecasting volatility, however, does not allow forecast volatility to change given historical information. GARCH models, introduced by Engle (1982) and generalised by Bollerslev (1986), Engle and Bollerslev (1986) and Taylor (1986), are specifically designed to model and forecast conditional variances. Volatility is modelled as a function of past values of the dependent variable and independent or exogenous variables.

In general form, the GARCH(p,q) model can be written as

$$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{3}$$

where equation (3) states that the conditional variance of stock market returns depends on some constant (ϖ), the previous period's squared random component of stock market returns (referred to as ARCH effects or the short-run persistence of shocks) and the previous period's variance (the contribution of shocks to long-run persistence, $\alpha + \beta$). Non-negativity of σ_t^2 requires that ϖ, α and β are

DOI: 10.1002/for

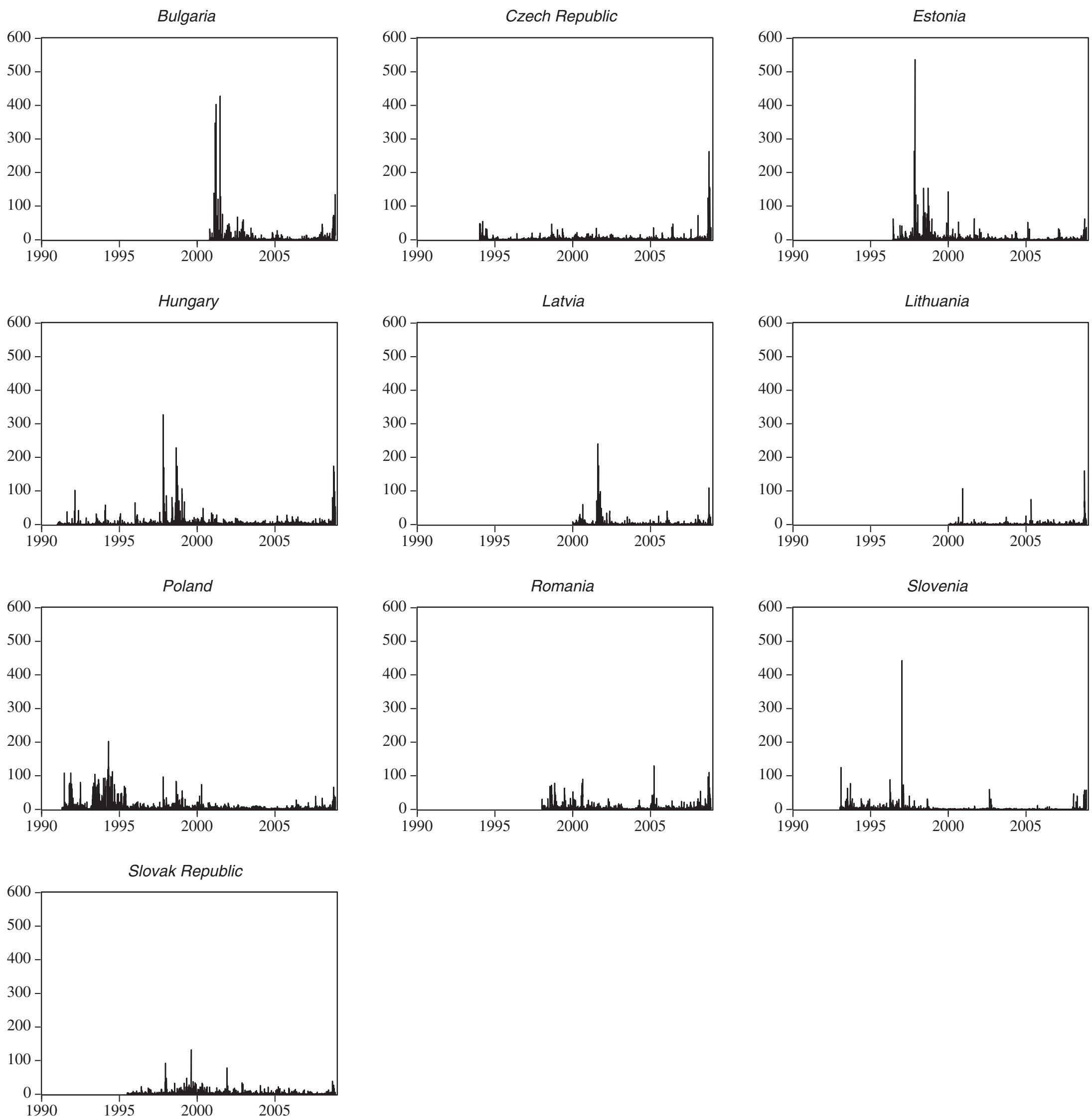

Figure 1. Plot of daily stock market volatility in Central and Eastern European countries

non-negative, while stationarity requires that $\alpha + \beta < 1$.[1] A value of $\alpha + \beta$ close to zero therefore implies that volatility persistence is high. The GARCH model is suitable when large changes in stock market returns are expected to be followed by further large changes.

The GARCH model assumes that negative shocks have the same impact on future volatility (symmetry) as a positive shock of the same magnitude. To allow for asymmetry (negative shocks have a

[1] It is also possible to consider so-called integrated GARCH models where $\alpha + \beta = 1$. However, in these models volatility shocks have permanent effects (see Engle and Bollerslev, 1986).

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Table I. Descriptive statistics of volatility

Statistic	Bulgaria	Czech Republic	Estonia	Hungary	Latvia	Lithuania	Poland	Romania	Slovenia	Slovak Republic
Mean	3.438	1.907	2.764	2.660	2.309	1.121	3.603	2.896	1.536	1.509
Median	0.323	0.352	0.264	0.437	0.262	0.174	0.565	0.587	0.144	0.168
Maximum	427.796	262.660	536.408	327.135	240.070	160.123	202.153	128.816	442.584	131.988
Minimum	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Standard deviation	18.308	7.912	14.472	10.968	10.317	5.503	10.743	8.079	9.053	4.796
Skewness	16.278	17.409	20.638	14.005	12.010	17.558	6.788	7.366	31.300	11.458
Kurtosis	327.210	430.970	634.645	281.673	199.587	404.224	66.213	76.020	1399.162	227.442
Observations	2111	3883	3255	4668	2321	2320	4590	2840	4140	3495
ARCH test (F-statistic)	156.593	467.626	81.509	774.125	559.958	351.798	144.290	494.650	561.471	17.915
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Note: p-value is given in square brackets.

DOI: 10.1002/for

larger impact on future volatility than positive shocks), Nelson's (1991) exponential GARCH model (EGARCH) can be employed. This model is given by

$$\log(\sigma_t^2) = \varpi + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{j=1}^{p} \alpha_j \left| \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right| + \sum_{j=1}^{r} \gamma_j \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \tag{4}$$

The EGARCH model is asymmetric as long as $\sum_j \alpha_j \neq 0$. When $\sum_j \gamma_j < 0$, then positive shocks generate less volatility than negative shocks. Asymmetry can also be modelled using the threshold GARCH model introduced independently by Zakoïan (1994) and Runkle *et al.* (1993). In this case, the specification for the conditional variance is given by

$$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{j=1}^{r} \gamma_j \varepsilon_{t-j}^2 \Gamma_{t-j} \tag{5}$$

where $\Gamma_{t-k} = 1$ if $\varepsilon_t < 0$, and 0 otherwise. In this framework, positive and negative shocks have differential effects on the conditional variance: $\gamma_j > 0$ would imply that negative shocks increase volatility and $\gamma_j = 0$ implies that shocks are symmetric.

Asymmetry can also be modelled using the power ARCH (PARCH) specification introduced by Ding *et al.* (1993). In the PARCH framework the power parameter δ is estimated rather than imposed, and optional parameters are added to capture asymmetry:

$$\sigma_t^\delta = \varpi + \sum_{j=1}^{p} \alpha_j (|\varepsilon_{t-j}| - \gamma_j \varepsilon_{t-j})^\delta + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta \tag{6}$$

where $\delta > 0$, $|\gamma_j| \leq 1$ for $j = 1, \ldots, r, \gamma_j = 0$ for all $j > r$ and $r \leq p$. As in the previous models, shocks are asymmetric if $\gamma_j = 0$.

Rather than assume that the conditional variance shows mean reversion to ϖ, which is constant for all t, following Engle and Patton (2001) the component GARCH model can be utilised to allow for mean reversion to a varying level, m_t. Using a GARCH(1,1) model, the component GARCH (CGARCH) can be expressed as

$$\begin{aligned} \sigma_t^2 - m_t &= \varpi + \alpha(\varepsilon_{t-1}^2 - \varpi) + \beta(\sigma_{t-1}^2 - \varpi) \\ m_t &= \omega + \rho(m_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \end{aligned} \tag{7}$$

The CGARCH approach would be appropriate if economic policies can result in reduced stock market volatility. One can also estimate the CGARCH model with a threshold, denoted by CGARCHT.

FORECASTING STOCK MARKET VOLATILITY

Comparison criteria

A number of criteria exist for evaluating the forecasting performance of volatility models (see Lopez, 2001, for a survey of these approaches). Each method has its own drawbacks, so, rather than choose between the approaches, the authors choose six loss functions:

$$\text{MSE1} = n^{-1} \sum_{t=1}^{n} (\sigma_t - h_t)^2 \tag{8}$$

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$$\text{MSE2} = n^{-1} \sum_{t=1}^{n} \left(\sigma_t^2 - h_t^2\right)^2 \tag{9}$$

$$\text{QLIKE} = n^{-1} \sum_{t=1}^{n} \left(\log(h_t^2) + \sigma_t^2 / h_t^2\right) \tag{10}$$

$$\text{R2LOG} = n^{-1} \sum_{t=1}^{n} \left(\log(\sigma_t^2 / h_t^2)\right)^2 \tag{11}$$

$$\text{MAD1} = n^{-1} \sum_{t=1}^{n} |\sigma_t - h_t| \tag{12}$$

$$\text{MAD2} = n^{-1} \sum_{t=1}^{n} \left|\sigma_t^2 - h_t^2\right| \tag{13}$$

Equations (8) and (9) are the usual mean squared error criteria. The metric QLIKE is the loss implied by a Gaussian likelihood, while the R2LOG loss function penalises volatility forecasts asymmetrically in low-volatility and high-volatility periods. The final two criteria (equations (12) and (13)) are the mean absolute deviation, which tend to be more robust in the presence of outliers than the MSE criteria.

To evaluate the hypothesis of whether some simple model is as good as any of the more complicated models in terms of expected loss, the Diebold and Mariano (1995) model (DM) is employed. The DM provides a useful framework within which to test relatively simple models (for example GARCH(1,1)) against more complex alternatives. The test compares a sequence of forecasts from model $k, h_{t+1}^2, \ldots, h_{t+n}^2$, to the conditional variance, $\hat{\sigma}_{t+1}^2, \ldots, \hat{\sigma}_{t+n}^2$, using a loss function L. Let the first model, $k = 0$, be the benchmark model that is compared to the other models, $k = 1, \ldots, q$. The forecast error function can be calculated as $L_t = g(e_{kt|k>0}) - g(e_{0t})$. The null hypothesis for forecast accuracy is that $E(L_t) = 0$; that is, the forecast error for model k is not significantly different from that of the benchmark model.

Defining the mean forecast difference as $\bar{L} = n^{-1} \sum L_t$, the tests take the h-step-ahead forecasts as autocorrelated up to lag h, and zero thereafter. The variance for $\bar{L}$ is estimated as $\nu(\bar{L}) \approx n^{-1}[\gamma_0 + 2\sum_{s=1}^{h-1} \gamma_s]$, where γ_s the autocovariance of the loss function, is calculated by $\widehat{\gamma}_s = n^{-1} \sum_{t=s+1}^{n} (L_t - \bar{L})(L_{t-h} - \bar{L})$. The DM test statistic can then be calculated as

$$\text{DM} = [\nu(\bar{L})]^{-1/2} \bar{L} \tag{15}$$

The DM statistic is $N(0, 1)$ and the variance is the Newey–West robust estimate.

Out-of-sample forecast results

All the empirical models outlined above and summarized in Table II, are used to provide out-of-sample forecasts for the period 1 January 2008 to 25 November 2008. The predictions from these models are then compared over weekly, monthly and quarterly trading horizons using the six comparison criteria outlined earlier (MSE1, MSE2, R2LOG, QLIKE, MAE1, MAE2). Relative forecast evaluation statistics—the forecast evaluation statistic of the model under consideration as a ratio of that for the naïve model—are averaged across the CEE countries. A value less than one suggests that

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Table II. List of volatility models

Naïve	$\sigma_t^2 = \varpi$
GARCH	$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$
Taylor/Schwert	$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \alpha_j \lvert\varepsilon_{t-j}\rvert + \sum_{j=1}^{q} \beta_j \sigma_{t-j}$
A-GARCH	$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \left[\alpha_j \varepsilon_{t-j}^2 + \gamma_i \varepsilon_{t-j}\right] + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$
Thr.-GARCH	$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{j=1}^{r} \gamma_j \varepsilon_{t-j}^2 \Gamma_{t-j}$
GJR-GARCH	$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \left[\alpha_j + \gamma_i I_{\{\varepsilon_{t-1}^2 > 0\}}\right] \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$
Log-GARCH	$\log(\sigma_t) = \varpi + \sum_{j=1}^{p} \alpha_j \lvert\varepsilon_{t-j}\rvert + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j})$
EGARCH	$\log(\sigma_t^2) = \varpi + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{j=1}^{p} \alpha_j \left\lvert\frac{\varepsilon_{t-j}}{\sigma_{t-j}}\right\rvert + \sum_{j=1}^{r} \gamma_j \frac{\varepsilon_{t-j}}{\sigma_{t-j}}$
A-PARCH	$\sigma_t^\delta = \varpi + \sum_{j=1}^{p} \alpha_j (\lvert\varepsilon_{t-j}\rvert - \gamma_j \varepsilon_{t-j})^\delta + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta$
CGARCH(1,1)[a]	$\sigma_t^2 - m_t = \varpi + \alpha(\varepsilon_{t-1}^2 - \varpi) + \beta(\sigma_{t-1}^2 - \varpi)$ $m_t = \omega + \rho(m_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$

[a] Model also estimated with threshold.

the model outperforms the naïve model. Given that each evaluation criterion may differ in its choice of the 'best' model, the authors also compute the average rank for each model based on their forecasting accuracy. The 'best' model therefore receives a score of 1, the second best a score of 2, and so on.

The results for relatively short horizons (trading week) are provided in Table III. Most models outperform the naïve model by at least 30% as reflected by MSE1, MSE2, MAD1 and MAD2. Over this period the EGARCH and PARCH models had the lowest median rank among the 12 volatility models considered. The superior performance of these two risk models suggests that capturing asymmetric volatility is quite important for predicting volatility in CEE countries. The simple GARCH model, however, despite not capturing these asymmetric effects, still performed relatively well, with a median rank of 5 over the six forecast evaluation statistics employed and the 12 volatility models considered.

In terms of predicting stock market volatility over a trading month, as expected, the predictive power of the models declines appreciably as reported in Table IV, but their performance was still superior to the naïve model. The asymmetric models, PARCH and EGARCH, were still among the top performers. However, the threshold models, as well as those that allow for a mean reverting volatility process, CGARCH and THRCGARCH, and the GJR model that allows for the effects of good and bad news on stock market volatility, also had relatively low median ranks in terms of predicting volatility. These models remained superior in terms of their predictive ability when the forecast horizon was widened to the trading quarter (see Table V).

To identify whether or not the forecast errors from the more sophisticated models are statistically different from those of the relatively simple GARCH(1,1) model, the DM test statistic is calculated for the 1-week trading horizon. The results are provided in Table VI. In most countries, the simple GARCH(1,1) model has expected forecast errors that are statistically different from those for more complex models. Indeed, in Bulgaria, Hungary, Lithuania, Poland and Romania, none of the DM statistics for the 12 volatility forecasting models considered are statistically significant.

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Table III. Out-of-sample forecasting accuracy (trading week)

One week	Relative evaluation statistic						Rank						Median rank
	MSE1	MSE2	QLIKE	R2LOG	MAD1	MAD2	MSE1	MSE2	QLIKE	R2LOG	MAD1	MAD2	
AGARCH	0.6831	0.594	3.003	0.858	0.720	0.646	8	6	7	11	8	7	8
APARCH	0.6969	0.628	3.946	0.848	0.725	0.663	10	10	10	8	9	10	10
CGARCH	0.6701	0.618	10.664	0.804	0.690	0.645	5	8	12	1	2	6	6
EGARCH	0.6490	0.572	1.772	0.837	0.697	0.623	1	1	3	3	3	2	3
GARCH	0.6632	0.589	3.482	0.841	0.702	0.627	4	3	9	6	5	3	5
GARCHM	0.7022	0.617	3.117	0.858	0.732	0.661	11	7	8	12	10	9	10
GJR	0.6884	0.620	1.638	0.854	0.742	0.677	9	9	2	10	12	11	10
LOGGARCH	0.6613	0.592	2.333	0.837	0.711	0.636	3	5	4	5	7	5	5
PARCH	0.6498	0.574	4.759	0.837	0.685	0.616	2	2	11	4	1	1	2
TAYLOR	0.7274	0.683	2.937	0.851	0.739	0.685	12	12	6	9	11	12	12
THRCGARCH	0.6814	0.629	14.889	0.820	0.702	0.653	7	11	13	2	4	8	8
THRGARCH	0.6718	0.590	2.622	0.845	0.704	0.631	6	4	5	7	6	4	6

DOI: 10.1002/for

Table IV. Out-of-sample forecasting accuracy (trading month)

	MSE1	MSE2	QLIKE	R2LOG	MAD1	MAD2	MSE1	MSE2	QLIKE	R2LOG	MAD1	MAD2	Median rank
AGARCH	0.9464	0.942	1.648	0.980	1.039	0.988	9	4	6	12	12	10	10
APARCH	0.9430	0.952	1.913	0.962	1.012	0.962	7	8	10	8	8	6	8
CGARCH	0.8856	0.936	3.856	0.911	0.941	0.918	2	2	12	1	2	2	2
EGARCH	0.9005	0.944	1.530	0.947	0.971	0.928	4	6	4	4	4	4	4
GARCH	0.9555	0.962	1.798	0.956	1.021	0.993	10	11	9	5	9	11	10
GARCHM	0.9582	0.955	1.619	0.977	1.036	0.982	11	9	5	11	11	8	10
GJR	0.8993	0.956	1.405	0.936	0.938	0.905	3	10	2	3	1	1	3
LOGGARCH	2.9121	18.694	1.527	0.970	1.322	2.315	13	13	3	10	13	13	13
PARCH	0.9168	0.941	2.129	0.956	0.998	0.959	5	3	11	6	5	5	5
RW	1.0000	1.000	1.000	1.000	1.000	1.000	12	12	1	13	6	12	12
TAYLOR	0.9277	0.943	1.763	0.958	1.010	0.970	6	5	8	7	7	7	7
THRCGARCH	0.8851	0.933	4.448	0.921	0.951	0.924	1	1	13	2	3	3	3
THRGARCH	0.9439	0.947	1.676	0.970	1.028	0.984	8	7	7	9	10	9	9

Table V. Out-of-sample forecasting accuracy (trading quarter)

	MSE1	MSE2	QLIKE	R2LOG	MAD1	MAD2	MSE1	MSE2	QLIKE	R2LOG	MAD1	MAD2	Median rank
AGARCH	0.903	0.985	1.300	0.984	0.974	0.954	7	3	2	11	10	9	8
APARCH	0.904	0.998	1.576	0.974	0.959	0.936	8	8	11	8	7	6	8
CGARCH	0.861	0.983	3.062	0.925	0.896	0.898	1	2	13	1	1	2	2
EGARCH	0.879	0.990	1.430	0.974	0.940	0.916	4	5	6	6	4	4	5
GARCH	0.914	1.007	1.560	0.955	0.950	0.959	11	12	10	3	6	10	10
GARCHM	0.911	0.998	1.333	0.983	0.971	0.948	10	9	3	10	9	7	9
GJR	0.866	0.999	1.350	0.974	0.931	0.893	3	10	4	7	3	1	4
LOGGARCH	2.271	14.175	1.362	0.982	1.177	2.003	13	13	5	9	13	13	13
PARCH	0.886	0.988	1.480	0.967	0.949	0.936	5	4	8	4	5	5	5
RW	1.000	1.000	1.000	1.000	1.000	1.000	12	11	1	13	12	12	12
TAYLOR	0.911	0.991	1.440	0.989	0.986	0.965	9	7	7	12	11	11	10
THRCGARCH	0.866	0.982	2.796	0.934	0.907	0.908	2	1	12	2	2	3	2
THRGARCH	0.900	0.991	1.520	0.972	0.962	0.949	6	6	9	5	8	8	7

Table VI. Diebold–Mariano test statistics (GARCH(1,1) used as benchmark model)

	BULX	CZEHX	ESX	HUNX	LATX	LITX	POLX	ROMX	SLEX	SLVX
AGARCH	−0.586	−2.021	−21.976	0.298	−0.387	−1.693	−1.500	0.698	−1.807	16.129
	[0.589]	[0.113]	[0.000]	[0.781]	[0.718]	[0.166]	[0.208]	[0.524]	[0.145]	[0.000]
APARCH	0.390	−0.547	3.507	0.193	3.251	2.232	−0.557	−0.674	−2.312	−16.306
	[0.716]	[0.613]	[0.025]	[0.856]	[0.031]	[0.089]	[0.607]	[0.537]	[0.082]	[0.000]
CGARCH	−1.014	0.590	− 8.966	−1.661	5.090	2.584	1.745	−1.635	−2.656	−8.199
	[0.368]	[0.587]	[0.001]	[0.172]	[0.007]	[0.061]	[0.156]	[0.177]	[0.057]	[0.001]
EGARCH	−0.174	−3.880	2.294	0.453	3.208	−1.683	−0.146	1.592	10.861	−12.301
	[0.870]	[0.018]	[0.084]	[0.674]	[0.033]	[0.168]	[0.891]	[0.187]	[0.000]	[0.000]
GARCHM	0.488	0.225	2.708	0.337	−0.859	2.098	−0.251	1.228	−1.600	13.628
	[0.651]	[0.833]	[0.054]	[0.753]	[0.439]	[0.104]	[0.814]	[0.287]	[0.185]	[0.000]
GJR	−0.411	−0.946	5.651	0.001	3.683	−1.251	−1.659	0.492	−0.610	17.765
	[0.702]	[0.398]	[0.005]	[0.999]	[0.021]	[0.273]	[0.173]	[0.649]	[0.575]	[0.000]
LOGGARCH	−1.026	0.044	18.670	−0.774	−1.002	2.420	0.342	0.610	−1.799	8.649
	[0.363]	[0.967]	[0.000]	[0.482]	[0.373]	[0.073]	[0.750]	[0.575]	[0.146]	[0.001]
PARCH	0.413	−2.295	3.422	0.399	1.640	−1.624	−0.556	−1.618	−2.210	4.200
	[0.701]	[0.083]	[0.027]	[0.710]	[0.176]	[0.180]	[0.608]	[0.181]	[0.092]	[0.014]
RW	1.081	−3.006	93.406	1.754	2.437	3.696	1.521	−1.591	28.268	29.268
	[0.341]	[0.040]	[0.000]	[0.154]	[0.071]	[0.020]	[0.203]	[0.187]	[0.000]	[0.000]
TAYLOR	−0.951	−3.029	0.996	0.696	0.387	−1.671	1.881	1.538	0.539	−7.710
	[0.395]	[0.039]	[0.376]	[0.524]	[0.718]	[0.170]	[0.133]	[0.199]	[0.619]	[0.002]
THRCGARCH	−1.356	1.262	− 3.679	−0.338	1.148	1.588	−0.325	−1.633	−2.786	−7.972
	[0.247]	[0.276]	[0.021]	[0.752]	[0.315]	[0.188]	[0.762]	[0.178]	[0.050]	[0.001]
THRGARCH	0.521	−1.613	− 1.973	0.708	−2.411	−1.681	−0.549	0.830	10.864	7.674
	[0.630]	[0.182]	[0.120]	[0.518]	[0.074]	[0.168]	[0.612]	[0.453]	[0.000]	[0.002]

Note: p-value is provided in square brackets below the test statistic.

Only in the cases of the Czech Republic, Estonia, Slovenia and the Slovak Republic can volatility forecasting models be identified that are statistically superior to the GARCH (1,1) model. In the Czech Republic, the EGARCH, PARCH, random walk and Taylor models had forecast errors that are statistically smaller than those from the benchmark model. In Estonia, AGARCH, CGARCH and THRCGARCH were statistically different from zero; and for Latvia, THRGARCH was the only model that was significant at normal levels of testing. For Slovenia and the Slovak Republic, APARCH, CGARCH and THRCGARCH were statistically different from zero in both cases. In addition to these three models, the PARCH model was significant at the 10% level of testing in Slovenia, while the EGARCH and TAYLOR models had statistically significant smaller forecast errors in the Slovak Republic.

CONCLUSIONS

Overall, we have examined the forecasting performance of several well-known modelling variants with respect to stock market volatility. The results verify the well-known result that the GARCH-type models, on average, outperform other popular, albeit naïve, forecasting models. Furthermore, we find clear evidence that incorporating some form of asymmetry over longer durations improves substantially the forecasting ability of volatility models. One possible explanation of this could be the presence of volatility feedback or leverage effects in the CEE markets. Another possible explanation could be the presence of structural changes in the CEE markets that are not taken into account and which the asymmetric variants are more equipped to handle. Answering which of the two possibilities contributes more to the forecasting performance of the asymmetric GARCH variants is an interesting area for future research. This is not only important as an academic exercise about volatility forecasts, but, more importantly, if structural breaks explain asymmetry over longer periods, accounting for these might provide a mechanism for increasing the robustness of forecasts in the likely event of a future (unanticipated) break.

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DOI: 10.1002/for