Department of
Economics and Finance

VOLATILITY FORECASTS FOR THE RTS STOCK INDEX: OPTION-IMPLIED VOLATILITY VERSUS ALTERNATIVE METHODS

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Abstract

This paper compares volatility forecasts for the RTS Index (the main index for the Russian stock market) generated by alternative models, specifically option-implied volatility forecasts based on the Black-Scholes model, ARCH/GARCH-type model forecasts, and forecasts combining those two using a mixing strategy based either on a simple average or a weighted average with the weights being determined according to two different criteria (either minimizing the errors or maximizing the information content). Various forecasting performance tests are carried out which suggest that both implied volatility and combination methods using a simple average outperform ARCH/GARCH-type models in terms of forecasting accuracy.

1. Introduction

Derivatives, and options in particular, have become increasingly sophisticated financial instruments designed to deal with the uncertainty resulting from volatile asset prices. A popular method for forecasting their volatility is the option-implied volatility (IV) approach introduced by Black and Scholes (1972), who analysed the efficiency of options market and derived the most commonly applied formula for the estimation of European option prices. The evidence on the forecasting performance of implied volatility is rather mixed, partly because of the different forecasting techniques used by researchers. Doidge and Wei (1998) reported that in the case of the Canadian stock market non-simultaneity of prices and a non-competitive trading environment led to a poor performance of the IV estimator. Canina and Figlewski (1993) and Day and Lewis (1992) showed that for S&P 100 stock index implied volatility does not contain any valuable information, and mentioned model misspecification and expiration day effects as possible reasons; they also concluded that the Treasury bill rate is not a good proxy for the rate faced by an options arbitrageur.

In contrast, other studies found that IV forecasts outperform time series volatility forecast. For example, Christensen and Prabhala (1998) reached this conclusion for the S&P 100 stock index, and argued that using non-overlapping samples was the reason for the efficiency and unbiasedness of IV forecasts. Neely (2005) detected a strong linkage between changes in implied volatility and important economic events for the three-month eurodollar interest rates.

This paper focuses on volatility forecasting in the case of the RTS Index, one of the most traded stock indices in Russia for which no previous evidence is available. Specifically, it carries out various tests to compare the volatility forecasts generated by alternative models, namely option-implied volatility forecasts based on the Black-Scholes model, ARCH/GARCH-type model forecasts, and forecasts combining the former two using a mixing strategy based either on a simple average or a weighted

2. Methodology

2.1 Sampling procedure

We choose the RTS Index as the underlying asset for a number of reasons. First, existing studies have typically analysed the forecasting performance of implied volatility in the case of the main American and European markets, whilst there is no evidence concerning the Russian one. Second, the RTS Index is one of the most representative ones for the Russian market. It is

2.2. Implied volatility forecasts

A European-style call (put) option gives the right, but not the obligation, to purchase (sell) an asset at a strike price at maturity date (Poon and Granger, 2003). For pricing such options the well-known Black–Scholes formula can be used (Black and Scholes, 1973). This is a partial differential equation, based on the idea that one can hedge by trading the underlying asset, which involves modelling a call option price C or a put option price P as follows (see Hull, 2008):

$$- \quad \frac{1}{2} \quad 2$$

$$— \quad \frac{1}{2} \quad 2 \quad 2 \frac{2}{\quad 2} \qquad — \qquad 0$$

:, where (4)

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{ ,

- the payoff of the option when the price of the underlying asset is S.

Second, for futures contract the spot price of the underlying asset is replaced by the discounted futures price (Black, 1976):

$$- \quad -$$ (5)

The model discussed above

the volatility of the underlying asset, σ, is constant;

the risk-free interest rate, r, is known and constant over time;

the underlying price follows the log-normal distribution;

the index pays no dividends;

there are no transaction costs or taxes;

the underlying asset is divisible;

there are no restrictions for short-selling;

there is continuous trading without arbitrage.

These are "ideal conditions" and violation of any of them will result in some inaccuracy in the estimated theoretical price. In practice at least some of them are not satisfied. For instance, consider the assumption of constant volatility. Options with different strikes but with the same time to maturity typically give different values for the implied volatility for the same underlying asset; in particular, options either deep in-the-money or out-of-the-money tend to produce higher values for the implied volatility; this phenomenon is known as "volatility smile". Let us analyse it in the specific case of the RTS options considered here, which expire quarterly (on the 3rd Thursday of March, June, September, December). Figures 1 to 4 show the relationship between implied volatility and the central strike, i.e. the strike closest to the settlement price of RTS futures, on two different dates, in the case of of

*Figura1 0 59.32 841.9 reW*nBTF9 12 Tf1 0 0 1 19.66 672.34 Tm0 g0 Gt21.66 672.34 Tm0 g*

2.3 Comparison

If all three hypotheses are satisfied and the model is found to be data congruent, the estimated coefficients and the residuals can then be used in mixed strategies for forecasting the actual volatility index.

ARCH/GARCH-type Forecasts

Next we analyse forecasts based on historical data generated from ARCH/GARCH models. As a first step we use the standard GARCH framework introduced by Engle (1982) and Bollerslev (1986). In line with most of the existing literature, a parsimonious GARCH(1,1) specification is

- EGARCH (Nelson (1991), which implies an exponential rather than quadratic leverage effect;
- IGARCH, which restricts the parameters of the standard GARCH model to sum up to one.

After obtaining the estimates for volatility based on the different ARCH/GARCH specifications, one can then run the same regression as before to assess the information content of the historical volatility for predicting the ex-post volatility (*Figure 5-6. B*):

$$[illegible]\ 2\ \ 3\ . \qquad (12)$$

where [illegible] stands for the ARCH/GARCH-type volatility estimate. As before, the estimated co[illegible] mixed strategies.

[illegible]C[illegible]ed [illegible]ation, which [illegible]s the information criteria (AIC, BIC) and [illegible]axim[illegible] squa[illegible] he IGARCH mod[illegible] efore this is th[illegible] forecasting com[illegible] se.

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Mixed Strategies

Mixed strategies aim at producing more accurate forecasts than those based on either implied volatility or ARCH/GARCH-type models, both of which have been shown to perform relatively poorly (see, e.g., Beckers (1981), Canina and Figlewski (1993), Doidge and Wei (1998)). The idea is to combine the information provided by the two approaches considered so far in order to obtain better forecasts.

To begin with, we apply the simple method developed by Vasilellis and Meade (1996). An equal weight is assigned to each of the two volatility measures (*Figure 5-6. C*):

$$0.5 \quad \cdot \quad \cdot \quad , \qquad (13)$$

where

σ_t^G is volatility estimated using the IGARCH(1,1) model at time t;

σ_t^{IV} is volatility estimated using the Black and Scholes model at time t.

It is a simple average of the two measures that assumes that they are both equally informative and that their respective informational content is constant over time.

By contrast, below we give a larger weight to the procedure with the lowest error term (from 9) and from(12)), where the weight of each method is calculated using the share of its inverse error (1) in the cumulative inverse error term (*Figure 5-6. D*):

$$\frac{1}{1 + 1} \qquad (14)$$

$$\frac{1}{1 + 1} \qquad (15)$$

Alternatively, one can assign weights using a different criterion, i.e. by maximizing the information content rather than minimizing the error term. In this case, the weights will be a function of the standardized estimated coefficients a_1 and a_3 from equations (6) and (9) respectively, namely (*Figure 5-6. E*):

$$\frac{3}{3 + 1} \qquad (16)$$

$$\frac{1}{3+1} \tag{17}$$

Actual and implied volatility in each case are shown in Figure 5 and 6 for call and put options respectively:

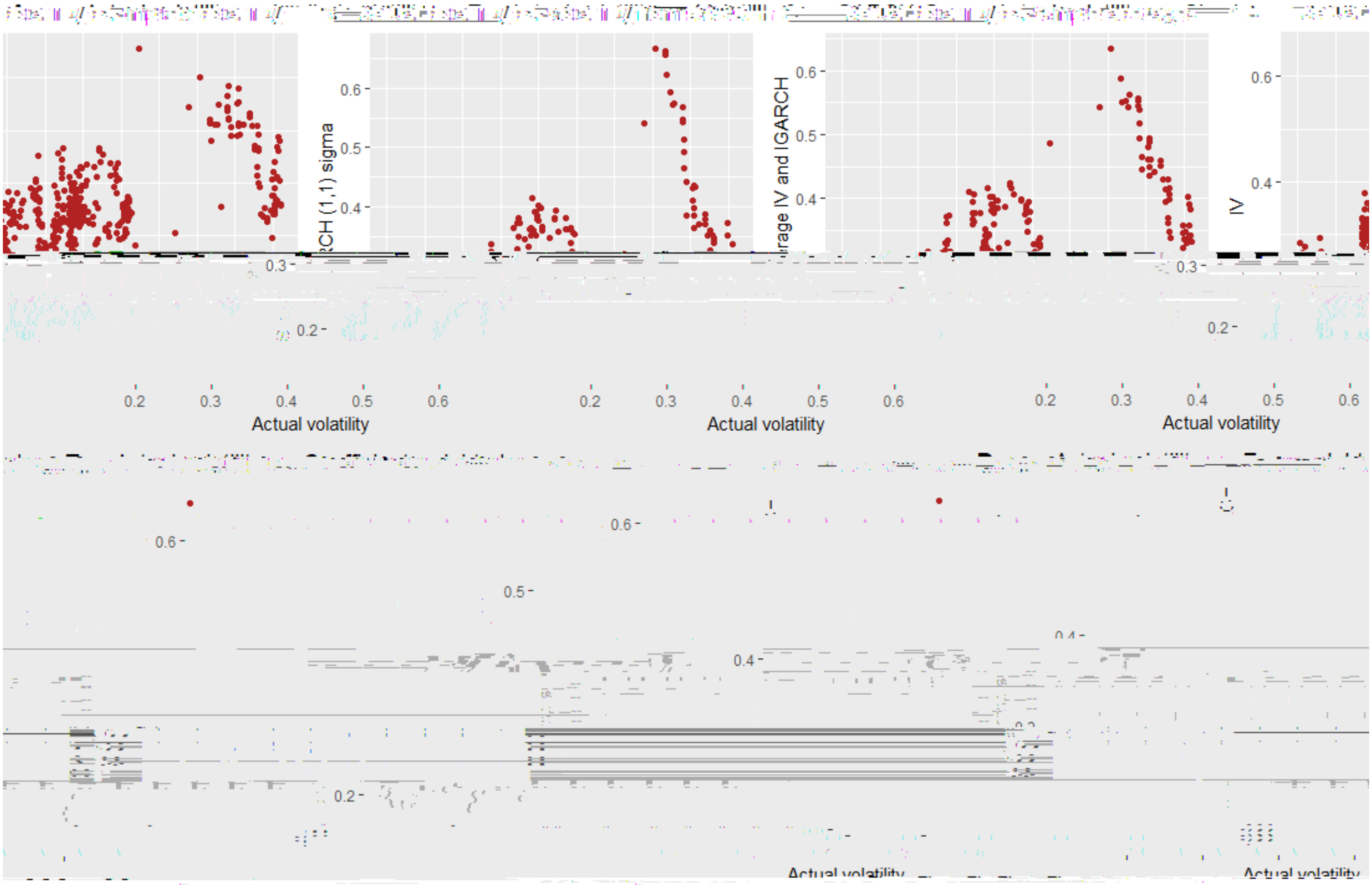

Figure 5. Regressions for Actual Volatility of the RTS Index Based on Data from Call Options

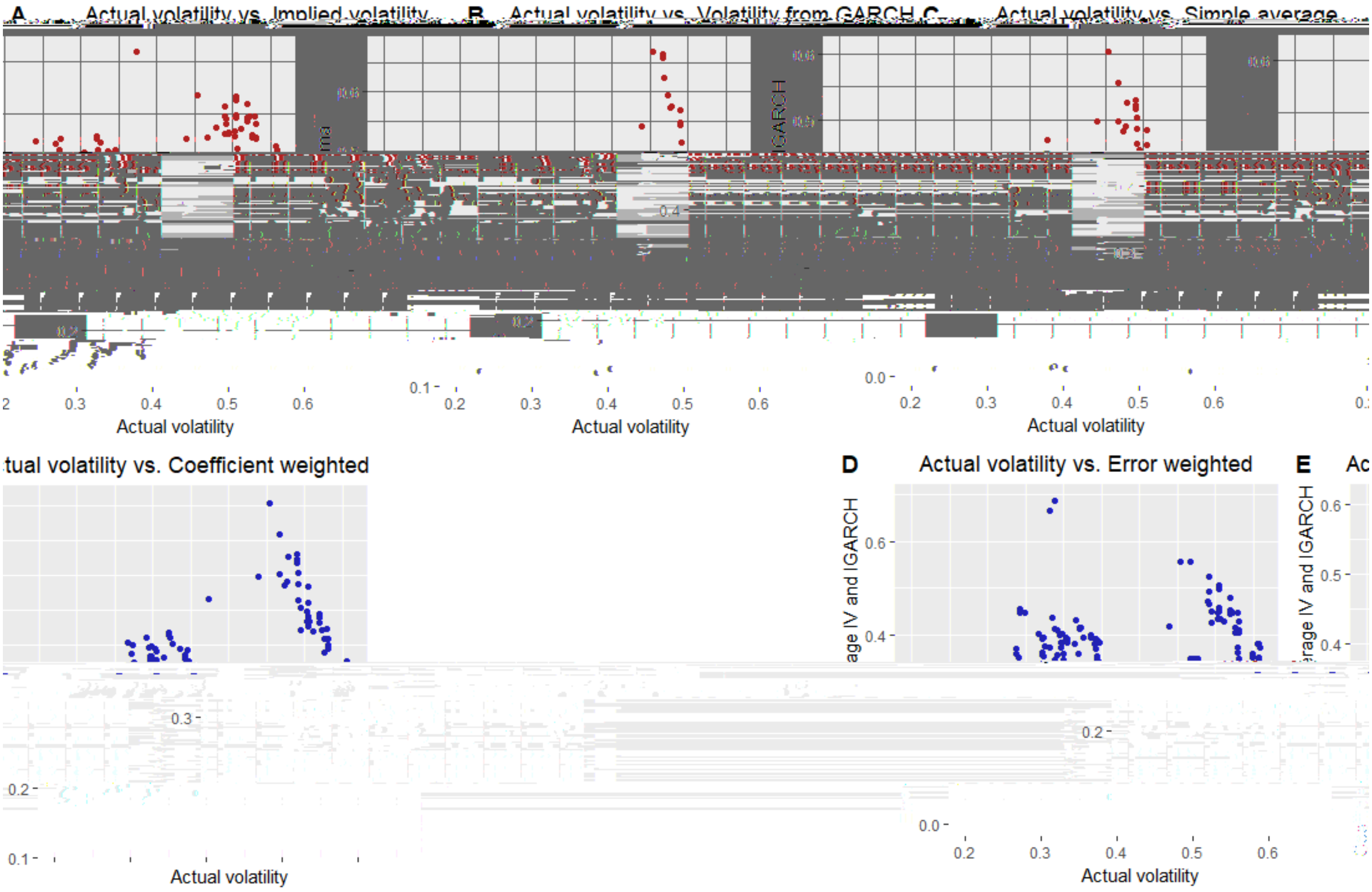

Figure 6. Regressions for Actual Volatility of the RTS Index Based on Data from Put Options

3. Forecasting Performance Comparisons

In order to assess the forecasting performance of the different methods considered above the sample is split into two: the first part of the sample period (from 5 January 2014 to 31 December 2016) is used to obtain in-sample estimates of the model parameters, and then out-of-sample forecasts (for the period from 1 January 2017 to 31 October 2018) are generated using a rolling window and are compared to the actual volatility measures.

Visual inspection of the estimated residuals in percentage terms (see Figure 8) suggests that predicted volatility is overestimated compared to the actual one by all methods.

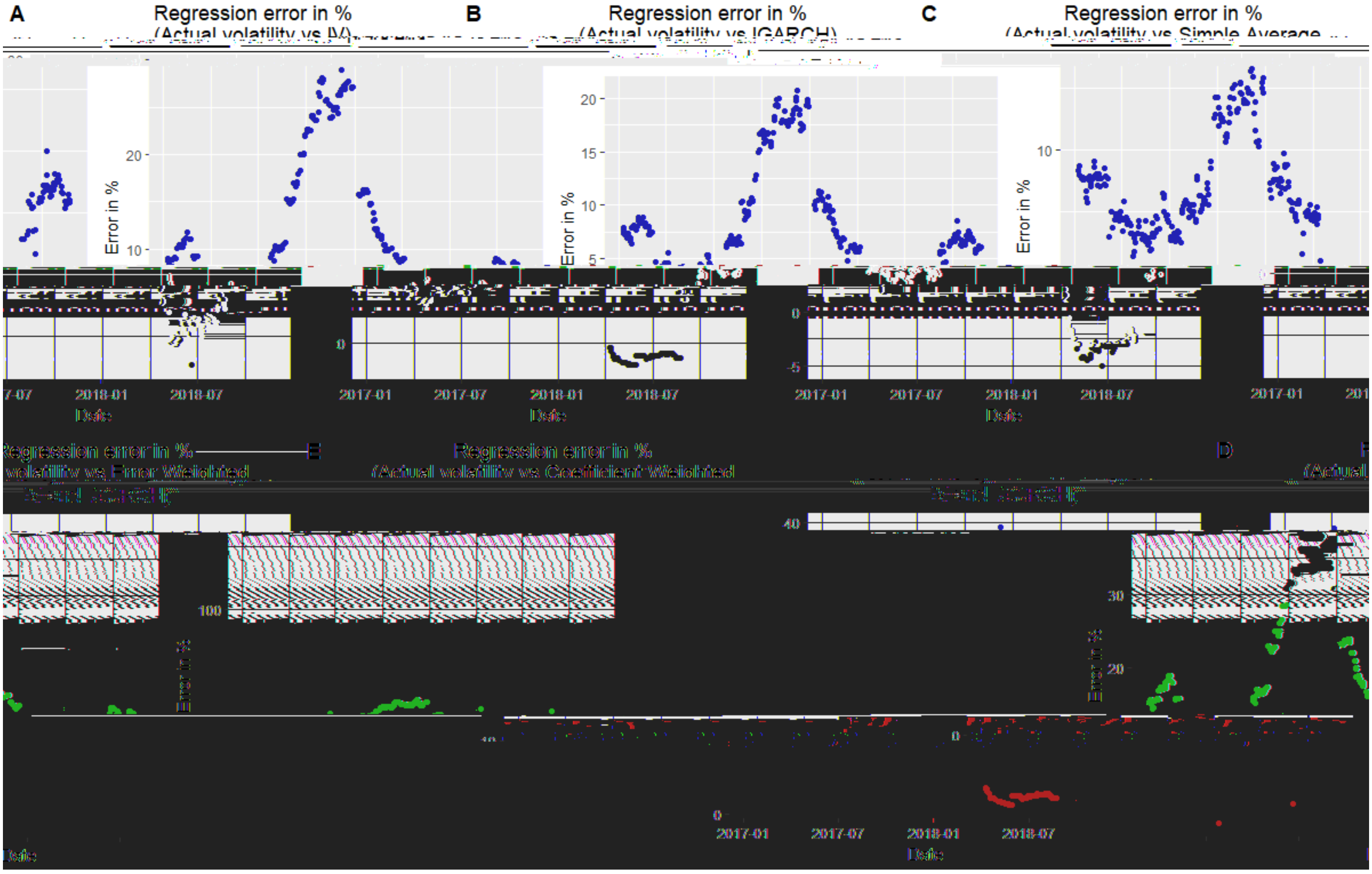

Figure 7. Error Term of Linear Regressions Based on Data from Call Options

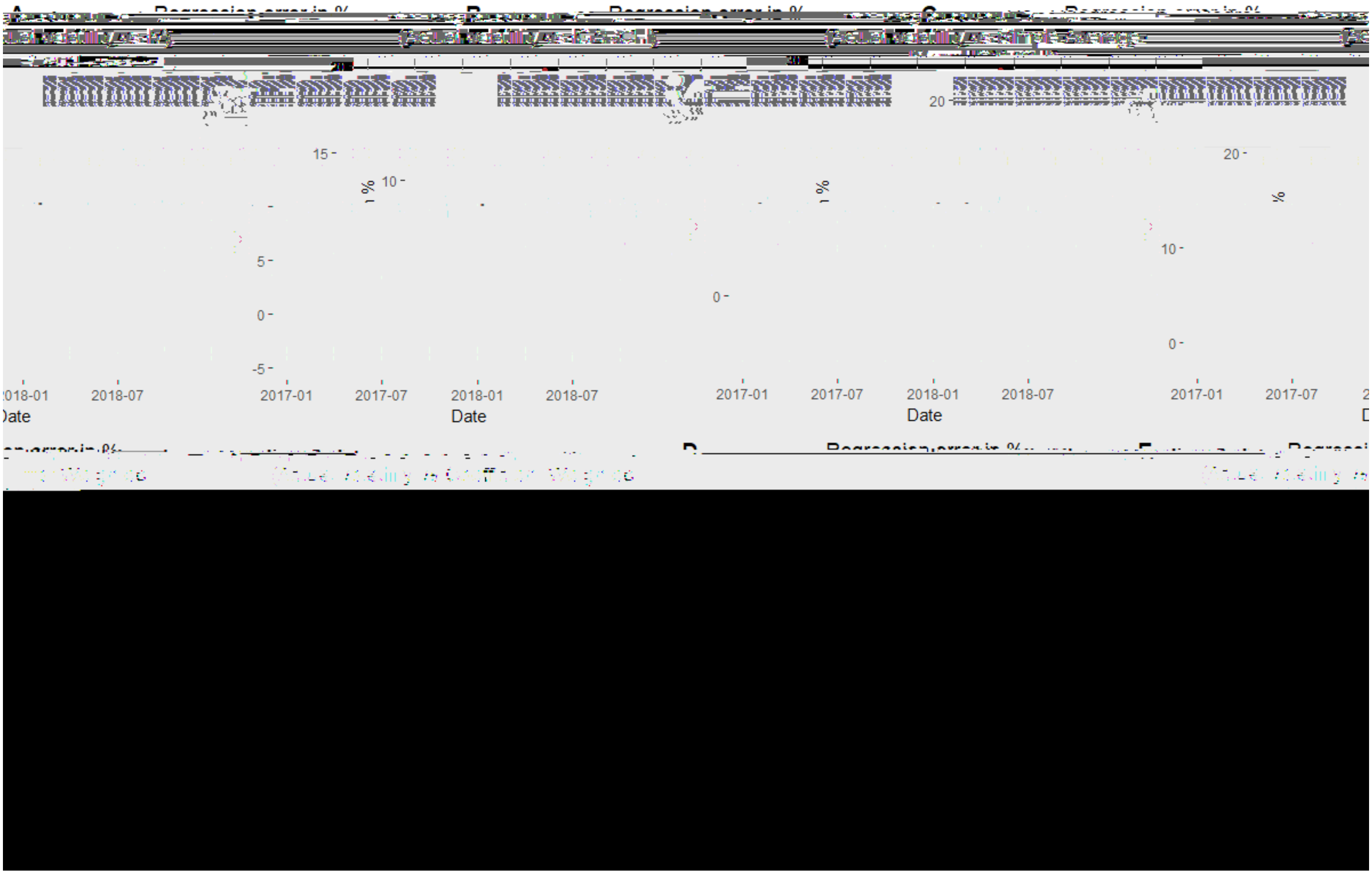

Figure 8. Error Term of Linear Regressions Based on Data from Put Options

The following forecasting performance tests are then carried out:

Mean absolute error: $\frac{1}{} \cdot \sum_{=1} | \quad |$;

Mean absolute percentage error: $\frac{100}{} \cdot \sum_{=1} \frac{}{}$;

Root mean square error: $\sqrt{\frac{1}{} \cdot \sum_{=1} {}^{2}}$,

where n is the number of predicted values, and N the total number of observations.

The results for call and put options are shown in Table 3 and 4, respectively.

Table 3. Forecasting Tests for RTS Call Options

Table 4. Forecasting Tests for RTS Put Options

The test statistics suggest that the implied volatilit The

Lewis C.M., Day T.E. (1992). *Stock market volatility and the information content of stock index options.* Journal of Econometrics, pp. 267-287.

Martens M., Zein J. (2004). Predicting financial volatility: High-frequency time-series forecasts vis-à-vis implied volatility. The Journal of Future Markets.

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