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Forecasting carbon futures volatility using GARCH models with energy volatilities

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ABSTRACT

This article examines the volatility forecasting abilities of three approaches: GARCH-type model that uses carbon futures prices, an implied volatility from carbon options prices, and the *k*-nearest neighbor model. Based on the results, we document that GARCH-type models perform better than an implied volatility and the k-nearest neighbor model. This result suggests that carbon options have little information about carbon futures due to their low trading volume. We also investigate whether the volatilities of energy markets, i.e., Brent oil, coal, natural gas, and electricity, forecast following day's carbon futures volatility. According to the results, we suggest that Brent oil, coal, and electricity may be used to forecast the volatility of carbon futures.

1. Introduction

GARCH-type models are widely used to estimate volatility of financial asset returns and show good performance. However, according to the survey results of Poon and Granger (2003), GARCH-type models are not necessarily the best forecasting model, as they give satisfactory results for in-sample forecasts, but not for out-of-sample forecast estimation. Generally, there are two alternatives to GARCH-type models: historical volatility and implied volatility (IV). The historical volatility approach predicts volatility using the past volatility of a sample. The random walk, historical average, simple moving average, exponential smoothing, exponentially weighted moving average, and *k*-nearest neighbor (k-NN) methods all belong to this approach. Apart from random walk and historical average, successful applications of the historical volatility approach normally involve searching for the optimal lag length or weighting scheme in an estimation period for out-of-sample forecasting. The second alternative to GARCH-type models, IV, uses the Black–Scholes option pricing formula. In this formula, all parameters other than volatility are observed in financial markets. After inserting these parameters into the Black–Scholes formula, volatility is the only unknown parameter. The formula is then inverted to derive an estimate of volatility implied by the observed option price. Eventually, an estimate of volatility becomes IV.

The choice of method to forecast returns volatility depends on comparing the performance of several alternatives. Poon and Granger (2003) point out that, in a forecasting exercise, comparing the forecasting performance of the different methods is most important. There are several approaches to assess the performance of forecasts. These approaches comprise computing the difference between the forecasts and the observed value, running regression to investigate the information content of forecasts, and measuring the relative usefulness of forecasts on the basis of a utility function or in relation to common uses of volatility forecasts in financial markets (Agnolucci, 2009). This article focuses on the first two of these approaches. Agnolucci (2009) indicates that these two approaches are traditional in financial econometric literature.

Although there are many studies on most financial assets, much remains to be done in the carbon market. The carbon market has been active under the EU Emission Trading Scheme (ETS) since 2005, after the Kyoto Protocol came into force. Under the EU ETS, spot, futures, and options of the EU allowance (EUA; the legal aspect) and Certified

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Emission Reduction (CER; the voluntary aspect) are traded, with the trading volume of the EUA being larger than that of CER.[1] Following the Kyoto Protocol, phase I was from 2005 to 2007, phase II from 2008 to 2012, and phase III is from 2013 to 2020. Following Daskalakis et al. (2009), there was a market correction which resulted from the inter-phase banking restriction and the over-allocation problem. However, since the advent of phase II, this restriction has moderated and the amount of the allocation has been adjusted (Chevallier, 2011b). Moreover, the trading volume and market evolution have grown since 2005.[2] Therefore, the carbon market is moving to mature state, and the econometric application to the carbon market is a valuable exercise. Here, we focus only on EUA futures in phase II because of its high trading volume.

The purpose of this article is to examine the predictive power of GARCH-type, IV, and k-NN models of EUA futures returns in phase II. The predictive power of each is assessed using various loss functions, such as the mean square error (MSE), MSE-LOG, mean absolute error (MAE), MAE-LOG, and QLIKE, as well as the regression-based approach, the Diebold–Mariano test, the superior predictive ability test, and the model confidence set. In GARCH-type models, we use various types of GARCH models and error distributions. Another contribution of this article is to investigate whether EUA futures volatility is related to energy market volatility. In contrast to previous literature, for example Chevallier (2009, 2010), and Chevallier and Sévi (2011), we first assess the relationship between EUA futures volatility and energy market volatility using the linear regression approach.

This article is organized as follows. Section 2 details the methodology used in this article and discusses previous literature. Section 3 describes the data used. Section 4 presents the results from the GARCH-type models estimation. Section 5 contains the results from the model comparison. Section 6 describes the results using GARCH-type model with energy volatilities. Section 7 concludes this article.

2. Methodology and literature review

To forecast the volatility of financial time series, various GARCH-type models have been used. The traditional GARCH(p,q) model, where p is the order of the moving average ARCH term and q is the order of the autoregressive GARCH term, can be written as (Bollerslev, 1986):

$$A(L)y_t = X_t^{'}\theta + B(L)\varepsilon_t, \tag{1}$$

$$\varepsilon_t = h_t e_t, \tag{2}$$

$$h_t^2 = \omega + \sum_{i=1}^{p}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=0}^{q}\beta_j h_{t-j}^2, \tag{3}$$

where the two terms $A(L)$ and $B(L)$ in Eq. (1) are two polynomials of lags, and X_t is a vector of exogenous variables. Using Eq. (3) in this simplest model, the current conditional variance is forecasted as the function of a constant term, ω, the ARCH term, ε_{t-i}^2, and the GARCH term, h_{t-j}^2. More complicated GARCH-type models improve Eq. (3) to explain the asymmetric effect. Following Chevallier (2009), GARCH-type models with the asymmetric effect provide the best fit to the carbon futures prices among other GARCH-type specifications. Therefore, we use GARCH-type models with the asymmetric effect to estimate the parameters of the volatility equation. Nelson (1991) proposes the Exponential GARCH (EGARCH) model as:

$$\log h_t^2 = \omega + \sum_{i=1}^{p}\alpha_i\left(\frac{\varepsilon_{t-i}}{h_{t-i}}\right) + \sum_{j=0}^{q}\beta_j \log h_{t-j}^2 + \sum_{i=1}^{p}\gamma_i\left[\left|\frac{\varepsilon_{t-i}}{h_{t-i}}\right| - E\left(\left|\frac{\varepsilon_{t-i}}{h_{t-i}}\right|\right)\right], \tag{4}$$

where γ_i shows the presence of the asymmetric effect. The Threshold GARCH (TGARCH) model by Zakoian (1994) can be written as:

$$h_t = \omega + \sum_{i=1}^{p}\left(\alpha_i^+\varepsilon_{t-i}^+ - \alpha_i^-\varepsilon_{t-i}^-\right) + \sum_{j=0}^{q}\beta_j h_{t-j}, \tag{5}$$

where $\varepsilon_{t-i}^+ = \max(\varepsilon_{t-i},0)$ and $\varepsilon_{t-i}^- = \min(\varepsilon_{t-i},0)$, i.e., the positive and negative parts of ε_{t-i}, respectively. Glosten et al. (1993) introduce the GJR-GARCH model as follows:

$$h_t^2 = \omega + \sum_{i=1}^{p}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=0}^{q}\beta_j h_{t-j}^2 + \sum_{i=1}^{p}\gamma_i\varepsilon_{t-i}^2\Gamma_{t-i}, \tag{6}$$

where $\Gamma_{t-i} = 1$ if $\varepsilon_{t-i} < 0$, and 0 otherwise. In the TGARCH and GJR-GARCH models, negative or positive values of ε_{t-i} indicate bad or good news, respectively. Although Chevallier (2011d), Feng et al. (2011), and Chevallier and Sévi (2011) do not use GARCH models, instead using non-parametric modeling, nonlinear dynamics, and the HAR-RV model, respectively, several studies have employed GARCH-type models to estimate carbon volatility. Paolella and Taschini (2008) and Benz and Trück (2009) use an AR(1)-GARCH(1,1) model to fit EUA spot return dynamics. Chevallier (2010) also uses an AR(1)-GARCH(1,1) model to estimate the volatility of EUA spot and futures. In Chevallier (2009), various types of GARCH models, including GARCH, EGARCH, and TGARCH, are employed to estimate EUA futures volatility. Mansanet-Bataller et al. (2011) use TGARCH(1,1) to fit the VAR(4) residuals of EUA futures, and Chevallier (2011b) detects volatility instability using an EGARCH(1,1) model.

Implied volatility (IV) measures the expected volatility of an underlying asset of options in the future. The simplest method to compute the IV of options on futures comes from Black pricing formula (Black, 1976). According to this formula, IV can be obtained by inverting $C = [FN(d_1) - KN(d_2)]e^{-rT}$ where C is the call price, F is the current futures price, T is the time to expiration of the call option, K is the strike price of the call option, r is the risk-free interest rate, and N refers to the cumulative normal distribution values at $d_1 = \left[\ln(F/K) + (\sigma^2/2)T\right]/\sigma\sqrt{T}$ and $d_2 = d_1 - \sigma\sqrt{T}$. The value of σ indicates the implied volatility of the underlying futures. We use this approach following Agnolucci (2009) and Chevallier (2011b). Chevallier (2011b) calculates the IV of carbon futures by minimizing the difference between real call option prices and Black call option prices.

In econometrics, the k-nearest neighbor method is used to estimate the density function of observed time series data (Silverman, 1986), or predict future value of given time series data. According to Clements and Hendry (2011), Farmer and Sidorowich (1987) introduce this method to the field of forecasting. When the k-nearest neighbor method predicts the volatility, this method uses the block values of previous volatility data. We consider a block of length m from the observed time series y_t, $t = 1,\cdots,T$, and denote it by $\mathbf{y}_t^m = (y_t, y_{t-1}, \cdots, y_{t-(m-1)})$. Therefore, there are $T - m + 1$ blocks. Then, according to the distance measure $d(\mathbf{y}_T^m, \mathbf{y}_t^m)$, we carry out a search to find the k earlier blocks that are closest to $\mathbf{y}_T^m$. The simplest distance measure is defined as $d(\mathbf{y}_T^m, \mathbf{y}_t^m) = \sum_{i=0}^{m-1}|y_{T-i} - y_{t-i}|$, and the k earlier blocks are the k nearest

[1] We can find this fact in several carbon trading exchanges, e.g., European Climate Exchange (ECX), Nordpool, European Energy Exchange (EEX), Powernext, and so on.

[2] ECX reports historical monthly trading volumes on their official website. According to ECX, the yearly trading volume in 2011 was approximately 71 times more than the trading volume in 2005. The World Bank reports carbon market evolution every year, and shows that the market evolution of 119.8 billion dollars in 2010 is about 15 times the 7.9 billion dollars in 2005.